

Advanced technologies for planning and operation of prosumer energy systems, volume II

Edited by

Bin Zhou, Junjie Hu, Liansong Xiong, Jian Zhao,
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Published in

Frontiers in Energy Research



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ISSN 1664-8714
ISBN 978-2-8325-3606-3
DOI 10.3389/978-2-8325-3606-3

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Advanced technologies for planning and operation of prosumer energy systems, volume II

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Citation

Zhou, B., Hu, J., Xiong, L., Zhao, J., Bu, S., Fang, J., Morais, H., Hou, P., eds. (2023). *Advanced technologies for planning and operation of prosumer energy systems, volume II*. Lausanne: Frontiers Media SA. doi: 10.3389/978-2-8325-3606-3

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An Optimal Hierarchical Pricing Strategy for Shared Energy Storage Services

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Keywords: hierarchical optimization, pricing strategy, shared energy storage, stackelberg game, trading framework

INTRODUCTION

Energy storage system (ESS) is a crucial part of intelligent grid. It plays a key supporting role in improving system efficiency. ESS has great potential applications in many scenarios, but it still faces challenges such as system framework design and operation strategy formulation in the future. In traditional framework design, consumers own and independently schedule the ESS, and have many difficulties with the high investment and management costs of the ESS (Dai et al., 2021). In general, shared energy storage system (SESS) can be treated as a problem of achieving efficiency and profit sharing (Noman et al., 2021). For example, a mainstream SESS structure, that is, installed in an energy community to serve many families was proposed (Müller and Welpel, 2018; Terlouw et al., 2019; Zhu and Ouahada, 2021). There are also many studies on the operation strategy of SESS. A strategy was proposed to manage SESS by aggregating controller to coordinate energy storage capacity (Dai and Charkhgard, 2018; Kalathil et al., 2019; Zhang et al., 2020). In (Terlouw et al., 2019; Murty and Kumar., 2020), an optimal method of SESS in grid-connected microgrid was proposed and the two-layer decision-making model to allocate the storage capacity was presented. Furthermore, multi-grade and multi-energy pricing and trading strategies were proposed in (Veeramsetty, 2021; Li et al., 2022; Zhang et al., 2022) to achieve the maximum of satisfaction and protection of participants' privacy.

In this paper, an energy trading framework is proposed for shared energy storage provider (SESP) and multi-type consumers aiming at improving utilization efficiency of SESS and the benefits of all participants. The opinions of this paper are twofold as listed: 1) An energy trading framework is proposed for SESP and consumers. Within the proposed framework, a system consisting of multiple consumers and SESS built between consumers is considered. Then, the provider makes full use of the time similarity characteristics of consumer load by formulating electricity price and optimizing the energy storage scheduling, so as to promote the utilization efficiency of energy storage and optimize the benefits; 2) An optimal energy pricing strategy is developed by constructing the trading framework as a bi-level optimization model. The energy optimal pricing strategy can benefit both provider and consumers and improves utilization efficiency. The upper-level problem aims to maximize the profits of provider, while the lower-level problem aims to get the optimal energy consumptions. The bi-level optimization model can be transformed as a single-level by shifting the lower-level problem with its Karush-Kuhn-Tucker (KKT) conditions.

HIERARCHICAL TRADING FRAMEWORK OF SHARED ENERGY STORAGE SYSTEM

The hierarchical trading framework among SESP, power utilities, and multi-type consumers is depicted in **Figure 1**. For the provider, it takes advantage of their scale to establish large-scale SESS

OPEN ACCESS

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Specialty section:

This article was submitted to
Process and Energy Systems
Engineering,
a section of the journal
Frontiers in Energy Research

Received: 13 June 2022

Accepted: 20 June 2022

Published: 11 July 2022

Citation:

Huang S, Gao X, Chen J, Chen R, Su Z
and Bao J (2022) An Optimal
Hierarchical Pricing Strategy for
Shared Energy Storage Services.
Front. Energy Res. 10:967998.
doi: 10.3389/fenrg.2022.967998

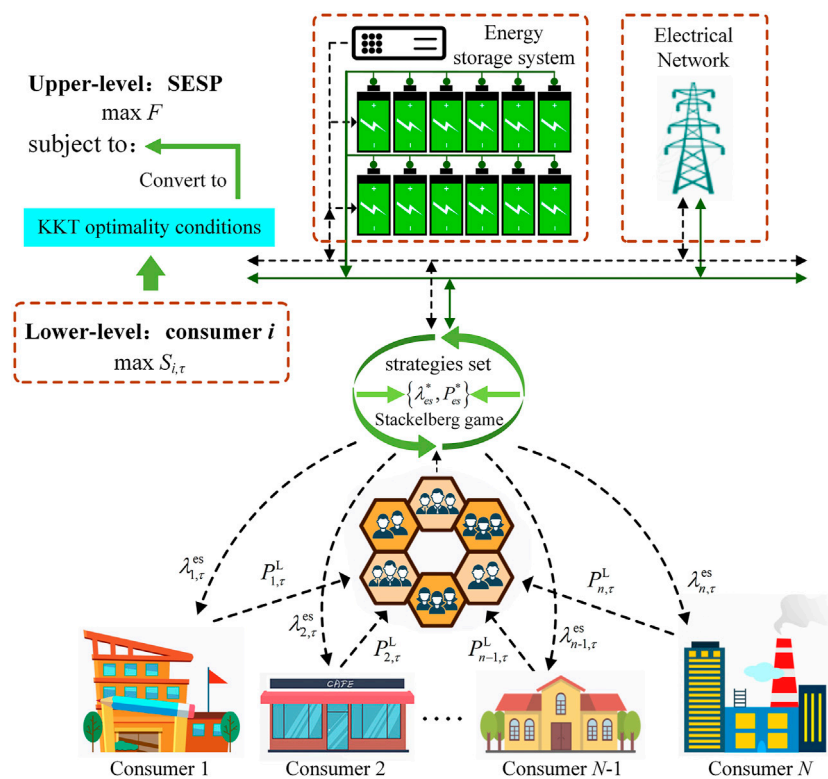


FIGURE 1 | Hierarchical trading framework of SESS.

among consumers, and manage them uniformly to provide shared energy storage services for multi-type consumers in the same distribution network area (Li et al., 2019; Zhu and Ouahada, 2021). In terms of demand side, consumers are willing to purchase electricity from the provider due to its price superiority and would trade electricity with power utilities once the power price released by power utilities is lower than that released by the provider (Zhao et al., 2014). In addition, consumers will trade with power utilities for its power shortage when the demand of consumers surpasses the supply of the provider.

The service objects of shared energy storage include residents, commercial consumers, and large industrial consumers. The consumers send their demand information to SESP, the provider extends the consumption behavior of the consumers in time and space, and gathers multiple similar consumers together to form a number of consumers clusters with a certain similarity. According to the results of similarity analysis, the provider sends service price information to consumers on the premise of achieving its own optimal profit. However, both consumers and provider aim to maximize their own interests. Provider should supply consumers with suitable prices to compete with power utilities. For example, consumers reduce the power purchased from provider, so that provider passively reduces its electricity prices. The interest optimization process of provider and consumers forms a game relationship. Provider strategically provides consumers with electricity prices

to maximize profits, while consumers influence provider by optimizing electricity consumption to maximize benefits. This is a sequential decision-making process, which constitutes a leader-follower game dominated by SESP, and can be expressed as a mathematical bi-level optimization model. The decision objective of upper model is to maximize the income of SESP to obtain the electricity price demanded by the provider. The decision objective of lower model is to maximize the satisfaction with energy consumption of consumers where the consumers adjust the strategy of their energy consumption according to the price. In the end, the optimal electricity price and the optimal discharge strategies set $\{\lambda_{es}^*, P_{es}^*\}$ are obtained in this cycle.

OPTIMAL PRICING STRATEGY BASED ON STACKELBERG GAME

From the perspective of consumers, different consumers choose to buy different amounts of energy according to their preferences for energy consumption. The utility can be defined as the satisfaction level of energy consumption. In this paper, a widely used quadratic function u is used to represent consumer's utility (Wu et al., 2020; Liu et al., 2022), which is strictly concave and continuously differentiable. Then, the consumer satisfaction function S is introduced, defined as the difference between utility and electricity consumption cost. It can

be described as a consumer satisfaction optimization problem. Since the demand of consumers is variable, consumers can always achieve optimal satisfaction by adjusting their demand to a point. When the marginal utility equals the energy prices, each consumer obtains the maximum satisfaction level based on optimality condition $\nabla S = 0$. SESP, as the provider of electricity, will produce costs during operation, including the operation and maintenance costs of battery energy conversion process and power supply costs from the power utilities. Hence, the profit of SESP F can be expressed as the difference between electricity sales and operating costs.

The electricity trading problem between SESP and consumers can be described as a Stackelberg game G with the provider as the leader and consumers as followers. The game G is defined as a set of strategies, including provider and consumers, where $\{\lambda_{es}\}$ is the strategy set of the provider; $\{P_{es}\}$ is the strategy set of consumers; $\{S\}$ is the satisfaction strategy set of consumers; $\{F\}$ is the profit of the provider.

$$G = \{(\mathcal{N} \cup \text{SESP}); \{F\}, \{\lambda_{es}\}; \{S\}, \{P_{es}\}\} \quad (1)$$

When all the participants in game G are at a Stackelberg equilibrium, SESP cannot improve its profit by adjusting energy prices from the Stackelberg equilibrium prices (λ_{es}^*), and similarly, no consumer can increase its satisfaction by adjusting its energy consumption (P_{es}^*). Based on the decision order, this game can be expressed as a bi-level optimizing model. In the upper-level, SESP finds the optimal energy prices (λ_{es}^*) by maximum F subjected to operational constraints. In the lower-level, consumers aim to get the optimal energy consumptions (P_{es}^*) by maximum S subjected to energy constraints. Note that consumers who have the approximate consumption energy similarity will get the same energy prices offered by the provider. Different group of consumers distinguished by consumption energy similarity will get different energy prices.

Due to its hierarchical structure and nonlinear objective function, the bi-level optimization problem cannot be directly solved by the available commercial solver. A common and accurate solution to this problem is to replace the lower-level problem by their KKT conditions. In this bi-level optimization problem, the optimal pricing strategy of SESP is composed of price variables, which are known parameters of the lower-level problem. In addition, when price constraints are given, the energy price set by the provider will always be lower than that set by the power utilities. Therefore, the bi-level optimization model can be transformed into a single-level optimization

model by KKT conditions. The key solving process for this problem as follows:

1) Initialize consumer electricity demand and service price parameters; 2) Formulate the model of Stackelberg game in which the SESP acts as the leader and consumers are the followers, and transform it into a bi-level optimization model; 3) Convert the lower-level problem to upper-level constraints by KKT optimality conditions, then transform the bi-level problem to a single-level problem; 4) Solve the single-level problem and obtain optimal strategies of the provider and consumers, then calculate the profit of the provider and the satisfaction of consumers.

DISCUSSION AND CONCLUSIONS

In this paper, an energy trading framework is proposed for SESP and multiple consumers. In terms of pricing, the similarity analysis method based on consumer load characteristics is introduced. When the consumer's load similarity is high, it means that the consumer's energy demand is relatively similar. The high similarity collection will make the peak-valley difference of the overall load more obvious. The provider can use the proportional coefficient method based on similarity to raise the electricity price and play the load transfer ability of energy storage. When the consumer's load similarity is low, the provider stimulates consumers' willingness to use energy by reducing the electricity price during this period, and improves the utilization rate of energy storage. In the end, the bi-level optimization problem is solved by Stackelberg game method, and the optimal pricing strategy is obtained. The proposed framework can achieve market equilibrium between provider and consumers and is of practical significance.

AUTHOR CONTRIBUTIONS

Writing the original draft and editing, SH; Conceptualization, XG and JC; Formal analysis, RC; Visualization and contributed to the discussion of the topic, ZS and JB.

FUNDING

This work is supported by the Scientific Research Startup Fund for Shenzhen High-Caliber Personnel of SZPT (No. 6022310042k).

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 27 June 2022
ACCEPTED 18 July 2022
PUBLISHED 11 August 2022

CITATION
Shi L, Guan X, Gao K, Pang L, Liu Y and
Xu Z (2022), Key technologies of rural
integrated energy system with
renewable energy as the main body.
Front. Energy Res. 10:979599.
doi: 10.3389/fenrg.2022.979599

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Key technologies of rural integrated energy system with renewable energy as the main body

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KEYWORDS

agricultural energy, integrated energy system, agrivoltaics system, renewable energy, carbon cycle

Introduction

The sustainability of energy and food supply has become a major concern in the world today. Renewable energy such as photovoltaic and hydrogen energy has developed rapidly in recent years because they do not emit carbon. Zhang et al. put forward a novel method for producing hydrogen energy, which not only reduces the cost of hydrogen energy but also consumes renewable energy (Zhang et al., 2022). The power of photovoltaic power generation may change rapidly with the change in weather, which brings great uncertainty to the operation of power networks (Fu et al., 2020a). When the solar radiation becomes sufficient, photovoltaic power generation surges up like the rising tide; when dark clouds cover the sun, photovoltaic power generation will fade as quickly as the ebb tide. Li et al. established a multi-level energy trading model to deal with the uncertainty of new energy in a market-oriented way (Li et al., 2022). Fu pointed out that statistical machine learning is an effective way to model the random characteristics of photovoltaic power (Fu, 2022a). Rural house roofs and agricultural greenhouse roofs provide a wide range of ground for photovoltaic installation. Given the disadvantages of petroleum agriculture, the application of photovoltaic power generation and hydrogen energy in modern agriculture has become the focus of attention in the field of agricultural energy. Despite the uncertainty in power, photovoltaic generation is an important scheme of a microgrid for remote rural areas far away from the power grid (Habib et al., 2021). In addition, the combination of hydropower and wind power can provide a reliable power supply for villages (Pathak et al., 2019). The combination of greenhouse and photovoltaic is called the agrivoltaics system, which has become a new and potential technology in agricultural energy systems (Riaz et al., 2022). It should be noted that agrometeorology has a direct impact on the agrivoltaics system. Not only the photovoltaic generation but also the crop needs solar radiation (Fu et al., 2020b). Li et al. carried out several sets of simulation experiments, which indicated that greenhouse artificial lighting can consume renewable energy (Li et al., 2021). With the development of agricultural energy and high-energy consumption agriculture in

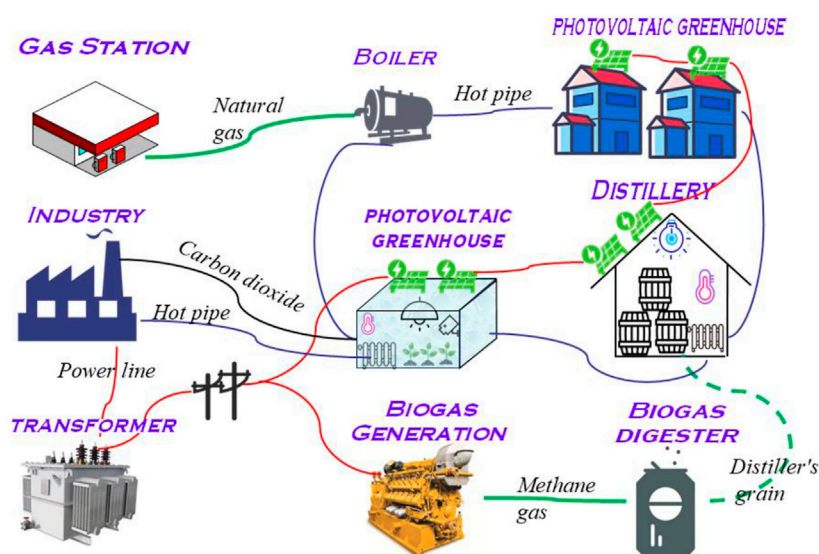


FIGURE 1
Schematic diagram of the rural IES in Qingdao, China.

villages, rural energy systems can have the function of a virtual power plant through load controls (Ju et al., 2022). Rural electrification not only occurs in agricultural planting but also fishery and aquaculture (Long et al., 2022). All-electric digital farms and all-electric digital fishing grounds have become rural-electrification programs, which have laid an engineering foundation for the theory of agricultural energy internet. The essence of agricultural energy internet means the integration of smart agriculture and smart grid in rural areas, and it is the inevitable result of the development of agricultural electrification and agricultural informatization (Fu and Yang, 2022). The fishery energy internet can deeply integrate power big data and fishery breeding so that fishermen can save money and labor (Fu, 2022b). The photovoltaic panel can change the amount of solar radiation on the water surface through angle change to shade the crabs cultured in the fish pond. At the same time, the ground source heat pump can be driven by photovoltaic power generation to adjust the water temperature. Wireless communication technology can improve the operational efficiency and security of the rural integrated energy system (IES) (Zhang, 2022). The deep integration of renewable energy, agriculture, and fishery industries, and the cluster development of the facility agriculture industry have an important effect on the economic operation mode of the rural IES. The requirements of agricultural planting, fishery, and aquaculture for energy quality vary greatly, which brings great challenges to the planning and control of the agricultural energy system.

Key technologies

Composition of rural IES

This paper studies a rural IES in Qingdao, China, as shown in Figure 1. The IES is composed of heat, electricity, and gas sources, which are used in agricultural production to improve energy efficiency, reduce environmental pollution and realize agricultural automatic production. Rural IES contains an ocean of renewable energy, including photovoltaic generation, biogas generation, and natural gas heating. The photovoltaic generation system can be placed on the roofs of villagers' houses, greenhouses, and distillery factories. Wine lees are generated during the fermentation, and they are transported to the biogas digester to supply biogas for power generation. The natural gas is supplied for gas-fired boilers to heat villagers' houses, greenhouses, and distillery factories in winter. The carbon dioxide produced by industry is transported to the greenhouses, and the carbon dioxide supplementation in the greenhouse provides a guarantee for the photosynthesis of crops.

We can realize the development of Shandong rural electrification from two aspects, including the construction of new energy and the transformation of distribution networks. The first way is to encourage the construction of renewable energy sources such as agricultural-photovoltaic complementarity projects and fishery-photovoltaic complementarity projects, which can be achieved through rural collective land shareholding and income sharing mechanisms. The second way is to implement upgrading projects of distribution networks so that each village has a reliable power supply network.

Synergy between agriculture and energy

The synergy between agriculture and energy includes many aspects, such as agricultural energy, agricultural production energy consumption, carbon-rich agriculture, etc. Agricultural biomass resources can be converted into energy, and energy is the escort of the facility's agricultural environment. Energy and agriculture also have carbon sink benefits. Specifically, the synergy technologies of agriculture and energy are as follows. 1) The first is carbon-rich agriculture technology. The use of carbon dioxide emitted from energy production in agricultural production can simultaneously solve the problems of the low-carbon energy systems and carbon dioxide fertilization, thus realizing a virtuous cycle of carbon emission from power generation to agricultural carbon fixation, and promoting the coordinated development of agricultural production and low-carbon energy. 2) The second is energy coupling technology, including agricultural energy and agricultural production energy consumption. On the energy side, agricultural energy includes crop straw power generation, rural biogas, biodiesel, fuel ethanol, etc. The development of agricultural biomass resources not only helps to solve the problem of agricultural waste pollution but also helps to solve the problem of energy shortage and carbon emissions. On the demand side, agricultural production energy consumption refers to the energy used in agriculture equipment working, which consumes energy to maintain the best environment in the greenhouses. The supply of the energy system should meet the agricultural energy demands. 3) The third is spatial coupling technology. The spatial coupling mode of the photovoltaic greenhouse brings about the problem of solar radiation competition between photovoltaic and crops. The coverage ratios of photovoltaic panels can change the greenhouse temperature and lighting. It is necessary to balance the lighting demands for photovoltaic generation and photosynthesis. The synergy between agriculture and energy is based on resource sharing and energy cascade utilization, that is, to use of differentiated space and energy demands to improve energy efficiency and agricultural output. The collaborative technology between agriculture and energy not only solves the single energy problem, but also takes on more responsibilities in the development of green circular agriculture, the comprehensive utilization of crop wastes, the reduction of agricultural non-point source pollution, and the protection of the ecological environment in rural areas.

Complementarity between agriculture and industry

There is a good complementary relationship between agricultural energy consumers and industrial energy consumers. Making good use of this complementary relationship can give full play to the environmental protection

of agriculture and the economy of industry, reduce carbon emission and improve the comprehensive utilization efficiency of multiple energy. Specific technologies of the complementarity between agriculture and industry include carbon cycle technology, thermal cycle technology, and renewable energy consumption technology. In terms of the carbon cycle, the food and cash crops in the greenhouse are varieties that absorb carbon dioxide, which can realize the local consumption of industrial carbon dioxide. The biomass waste in the greenhouse can be used for power generation and heat supply, which can compensate for parts of the power and heat demands of the greenhouse, and also produce carbon dioxide as fertilizer. The flue gas discharged from high carbon emission industries can be used to manufacture carbon dioxide fertilizer through the processes of desulfurization, denitration, and carbon dioxide capture. In terms of the thermal cycle, the greenhouse can use industrial waste heat as the heat source for maintaining the thermal environment of the facility's agriculture. Through light-temperature coupling and waste-heat recovery, the energy consumption level of the greenhouse can be greatly reduced, so as to reduce its operation cost. It has positive practical significance for the promotion and application of fully automatic control greenhouses. In terms of renewable energy consumption, facility agricultural load is a unique meteorological sensitive load, which has a certain matching relationship with renewable energy. The high energy consumption and cluster production mode of modern agriculture provides a way for the local large-scale consumption of new energy. In addition, the supplementary lighting and irrigation are time-shifting loads, which can be controlled to consume renewable energy. The differentiated demands of industry and agriculture for energy and carbon dioxide provide an opportunity for the complementarity between industry and agriculture, and the complementary project between industry and agriculture has broad prospects for development in the future.

Applications of biomass energy

Biomass energy is a zero-carbon fuel, which not only has no carbon emission but also can be obtained in local rural areas. There are many feasible ways to develop biomass energy. 1) Each village should build a factory to realize the molding and granulation of dry biomass materials under economically feasible conditions. A large biomass gas station should be built for one million hectares of farmland to handle a large number of wet biomass materials. 2) Large biomass boiler combustion equipment can realize the large-scale consumption of various biomass resources, and then the production cost of biomass gas can be cut and no greater than natural gas. 3) Biomass materials are by-products of rural life and agricultural production, and the treatment of these products needs to avoid emitting carbon dioxide. The

traditional methods are returning straw to the field or stacking green manure, resulting in emitting a certain amount of greenhouse gases. Converting biomass materials into biomass gas can avoid the emission of greenhouse gases. 4) Rural cooking, hot water, and heating are the primary energy loads of rural life, and biomass energy can meet the quality needs of rural domestic energy. We use livestock manure and straw as raw materials to ferment biogas and purify it to form biogas. Biogas can be used as boiler fuel or incorporated into the township gas pipe network to provide combustible gas.

Coal-fired power plants consume an ocean of mineral resources, but renewable energy such as wind power, photovoltaic, and biomass energy just needs natural resources such as space and solar radiation. Compared with crowded cities, rural areas have vast and abundant natural resources. Photovoltaic panels can be installed on the roofs of rural houses, greenhouses and livestock facilities, and open spaces. Wind power generation can be installed in rural areas with abundant wind resources. Small hydropower generating units can be installed in rainy mountain villages. The by-products of agriculture, forestry, and animal husbandry can provide rich resources for renewable energy power generation.

Discussion

With the development of modern agricultural industrial parks, energy production and consumption in rural areas show many new characteristics. The high energy consumption mode with high pollution is difficult to meet the needs of economic development in rural areas. There are a lot of renewable energy resources in Chinese villages, and the utilization of rural energy tends to be centralized. However, the utilization of rural energy is often developed and planned independently, leading to a large amount of energy waste, extremely low energy efficiency, and weak overall security and self-healing ability.

The rural revitalization strategy requires the development of renewable energy, which not only conforms to the development trend of China's energy strategy but also helps to reduce energy bills. The development of rural renewable energy should be in accordance with the general requirements of local conditions, policies, multiple-energy complementary, and efficiency. The utilization of green energy such as photovoltaic, biomass, and natural gas is an important part of the rural energy strategy. Specifically, the intensive development of distributed PV can be used as a primary energy source in Chinese villages. Natural gas should completely replace coal, and clean energy heating needs to be fully realized in rural areas.

With respect to power grid planning, the significant difference between the industrial energy system and agricultural energy system is that seasonal changes need to be well-considered and modeled in agricultural power grid planning, while an industrial load is not sensitive to seasons. This electricity demand for industrial products will not change significantly due to the weather, but the energy

consumed by crops in different seasons varies greatly as they are very sensitive to weather changes.

Conclusion

In view of the rural modern agricultural park scenario, this paper proposes key technologies for the planning and design, operation control, virtual power plant, etc. of the rural comprehensive energy system with renewable energy as the main body. The key technology development of rural IES needs to fully consider the controllability of the facility's agricultural environment and the physiological characteristics of crops. The uncertainty of renewable energy and seasonal agricultural load should be modeled, and we should put forward a complete set of technical schemes for planning and design, operation control, and virtual power plant in the rural IES. The research on rural IES in this paper provides feasible ideas and schemes for implementing the strategic objectives of carbon peaking and carbon neutralization and promoting the comprehensive development and diversified utilization of rural green energies.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Funding

This study is supported by the Science and Technology Project of State Grid Shandong Electric Power Company (520602210010) Qingdao Power Supply Company.

Conflict of interest

LS, XG, YL, and ZX were employed by State Grid Shandong Electric Power Company Qingdao Power Supply Company.

KG and LP were employed by Qingdao Anjie Energy Technology Co., Ltd.

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OPEN ACCESS

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 04 July 2022
ACCEPTED 18 July 2022
PUBLISHED 15 August 2022

CITATION
Zheng Y, Zhang E and An P (2022),
Peafowl optimization algorithm based
PV cell models parameter identification.
Front. Energy Res. 10:985523.
doi: 10.3389/fenrg.2022.985523

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Peafowl optimization algorithm based PV cell models parameter identification

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Photovoltaic (PV) power generation can considerably reduce the consumption of traditional fossil energy and improve environmental problems. Reliable photovoltaic (PV) cell modelling owns great significance to the following output characteristics analysis and optimal operation of the whole PV system, while there are several unknown physical parameters within different PV cell models. Thus, the identification of the internal parameters of the PV cell model is the first and foremost step for PV cell modelling, nevertheless, the intrinsic highly complex and non-linear and multi-modal features make traditional approaches, such as analytical methods hard to achieve satisfactory performance in solving this problem. Hence, this work aims to employ a powerful tool to effectively and efficiently overcome this thorny problem based on the most advanced optimization method. A recently developed meta-heuristic algorithm called peafowl optimization algorithm (POA) is employed in this work for PV cell modelling parameter identification. For comprehensive validation, two different PV cell models, i.e., double diode model (DDM) and triple diode model (TDM) are utilized. Simulation results demonstrate that POA can more accurately identify the unknown parameters of PV cell models in a higher convergence speed compared against other algorithms.

KEYWORDS

PV power generation, PV cell modelling, parameter identification, peafowl optimization algorithm, meta-heuristic algorithm

Introduction

Due to the high speed of technological development in the world today, the over-exploitation of fossil energy sources has led to the subsequent depletion of resources and air pollution, which has become a vital task to be resolved. In order to relieve the pressure of energy supply as soon as possible and effectively, the change of energy structure in the new era is necessary for the construction and development of the current society (Zhang et al., 2020), and the development of various green and efficient renewable energy and clean energy technologies is very important. Among them, solar energy has been widely used in various application scales and purposes thanks to its excellent characteristics (Jordehi, 2016), such as rich reserves, clean and safe, no pollution to the environment during power generation, low cost, convenient and simple installation, etc.

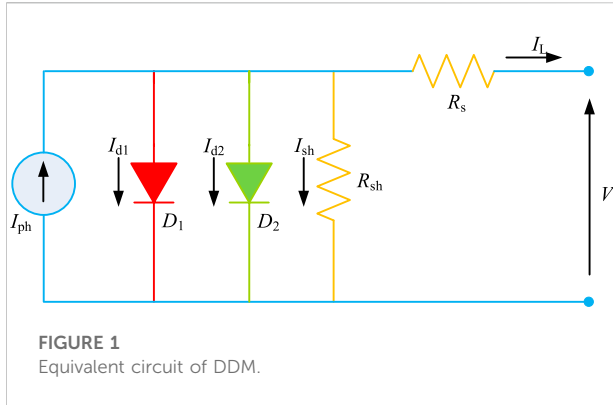
Although PV power generation has achieved good results so far, it still faces many problems and challenges (Abbassi et al., 2018). First of all, the manufacturer does not usually provide comprehensive PV cell parameters, which are derived from standard test conditions that do not accurately reflect the changes caused by subsequent failure and ageing of PV panels (Qais et al., 2019). Therefore, it is difficult to achieve reliable PV cell modeling, which affects the following control and optimization of the whole system (Chen et al., 2018; Li et al., 2018). Therefore, it is of great significance to develop an accurate and efficient intelligent identification algorithm to reliably identify the unknown parameters of PV cells, so as to achieve accurate modeling of PV cells. Due to the multimodal and highly nonlinear characteristics of photovoltaic systems, researchers in recent years have focused on various types of photovoltaic models. The most representative equivalent models are the single diode (SDM) and the double diode model (DDM). However, complex photovoltaic parameter models also have certain reference significance, such as the three-diode model (TDM) with a large number of unknown parameters. The problem of this model is that the calculation process is complicated. In particular, this paper proposes TDM as the research object, which can effectively analyze the complex physical problems existing in photovoltaic systems. In addition, in the diagnosis and analysis of photovoltaic system faults, it is necessary to accurately extract the relevant electrical parameters of the model. This method is an important prerequisite for accurate maximum power point tracking. So far, scholars at home and abroad have developed many methods to solve the highly nonlinear and multimodal problem of PV cell parameter identification (Pourmousa et al., 2019). These methods can be divided into three categories, namely, analytical method, deterministic method and heuristic algorithm. The first two methods have obvious defects in the process of solving problems, such as low identification accuracy, large amount of calculation, strong model dependence, and extremely sensitive to initial operating conditions and gradient information. At first, the analytical method was used to extract model parameters (Wolf and Benda, 2013), and a series of interdependent mathematical equations were used to correlate different model parameters (Torabi et al., 2017). Most of the parameters used are: 1) short-circuit current, 2) open circuit voltage and 3) maximum power point voltage and current, and appropriate equations are derived with the data provided by the manufacturer. However, using mathematical methods to solve these equations will cost a lot of time and energy, and the accuracy is limited (Villalva et al., 2009). In order to overcome the shortcomings of analytical method, deterministic method is applied to this problem. This kind of method is an optimization method to extract parameters based on some reference points on the given current-voltage (I - V) curve (Gao et al., 2016). This method makes use of the two important analytical properties of convexity and monotonicity of

the problem, which leads to two important research directions, convex function difference optimization method and monotone optimization method. Deterministic methods mainly include several types of traditional methods, including Lambert W-functions (El-Fergany, 2021) and iterative curve fitting (Chaibi et al., 2020), can effectively improve the calculation accuracy. However, they are very strict with the continuity, convexity and differentiability of the model characteristics and the objective function, and they are highly sensitive to gradient information and initial conditions, so they are easy to converge prematurely and fall into local optimization when solving highly nonlinear problems.

Meta-heuristic algorithms can transform the difficult problem of model parameter identification into a simple nonlinear constrained optimization problem. The great advantages of using meta-heuristic algorithm are: easy to implement, high efficiency, insensitive to initial conditions and gradient information, which can effectively avoid the shortcomings of the above two methods. They are considered to be the most promising and effective tool for PV cell parameter identification with the best comprehensive performance (Chan et al., 1986). So far, many heuristic algorithms have been used to identify the unknown parameters of PV cells (Pillai and Rajasekar, 2018; Yang et al., 2020), e.g., genetic algorithm (GA) (Jervase et al., 2001), particle swarm optimization (PSO) (Ye et al., 2009), artificial bee colony (ABC) (Oliva et al., 2014), whale optimization algorithm (WOA) (Xiong et al., 2018), backtracking search algorithm (BSA) (Yu et al., 2018), moth flame optimizer (MFO) (Allam, Yousri, Eteiba), etc.

However, not all metaheuristic algorithms can be used for any optimization problem, because the optimizer in each algorithm mechanism cannot make the most rational optimization results for all problems. Especially due to various intractable problems such as high nonlinearity and multimodality. Therefore, the problem that has been widely concerned is how to solve the practical engineering problems and ensure the optimization effect at the same time. In particular, this paper aims to propose a novel bionic optimization algorithm to achieve efficient and reliable optimization to solve the above highly complex practical engineering problems. Therefore, in this paper, a novel biomimetic optimization algorithm (POA) is used in the parameter identification of photovoltaic cell models, which has the following three contributions:

- POA is developed based on peafowl behavior which contains a variety of update factors that can effectively balance local exploration and global exploitation, thereby obtaining a satisfactory global optimal solution;
- POA with adaptive search is capable of dynamically adjusting its behavior to collect satisfactory search results at multiple stages;



- For PV cell parameter identification, two benchmark PV cell models, DDM and TDM, are used to comprehensively verify the effectiveness and reliability of POA for PV cell parameter identification. Case studies show that POA can effectively improve the accuracy and stability of parameter identification compared with other algorithms.

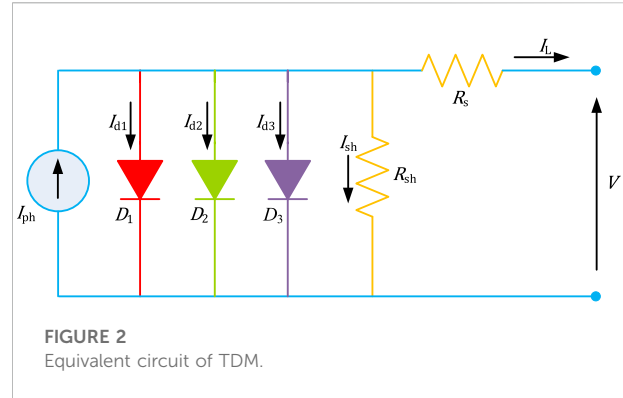
Photovoltaic cell modelling

Building an exact PV cell model (Chen and Yu, 2019) is fundamental to its subsequent studies of output characteristics, fault diagnosis, etc. Only by accurately fitting the output I - V and power-voltage (P - V) curves of PV cells can the performance of PV systems be reliably evaluated and predicted, which largely depends on accurately identifying the required physical parameters from the PV cell model. In this paper, two kinds of equivalent circuit models, DDM and TDM are selected for modelling.

Double diode model

As demonstrated in Figure 1, DDM consists of an ideal constant current source I_{ph} , a series resistance R_s , a shunt resistance R_{sh} , and two diodes D_1 and D_2 connected in parallel [(Pourmoussa et al., 2019)]. In particular, the series resistance R_s represents the total series resistance of material body resistance, thin layer resistance and electrode contact resistance. At the same time, parallel resistance R_{sh} is mainly caused by the poor p-n junction or impurities near the junction, which reflects the leakage level of the battery. R_{sh} affects PV cell open circuit voltage, the decrease of R_{sh} will reduce the open circuit voltage, but the short-circuit current will not be affected.

$$I_L = I_{ph} - I_{d1} - I_{d2} - I_{sh} \quad (1)$$



where I_{sh} denotes shunt resistance current R_{sh} ; and the currents I_{d1} and I_{d2} flowing through diodes D_1 and D_2 are written as (Abbassi et al., 2018)

$$I_{d1} = I_{sd1} \left[\exp \left(\frac{V_L + I_L R_s}{a_1 V_t} \right) - 1 \right] \quad (2)$$

$$I_{d2} = I_{sd2} \left[\exp \left(\frac{V_L + I_L R_s}{a_2 V_t} \right) - 1 \right] \quad (3)$$

Hence, output I - V relationship of DDM can be calculated by

$$I_L = I_{ph} - I_{sd1} \left[\exp \left(\frac{q(V_L + I_L R_s)}{a_1 V_t} \right) - 1 \right] - I_{sd2} \left[\exp \left(\frac{q(V_L + I_L R_s)}{a_2 V_t} \right) - 1 \right] - \frac{V_L + I_L R_s}{R_{sh}} \quad (4)$$

Thus, seven parameters need to be identified for DDM, e.g., I_{ph} , I_{sd1} , I_{sd2} , R_s , R_{sh} , a_1 , and a_2 .

Triple diode model

The configuration of TDM is illustrated in Figure 2. Compared with DDM, a third diode is added in parallel due to the influence of grain boundaries and large leakage current (Qais et al., 2019).

Similarly, output I - V relationship of TDM is calculated by (Qais et al., 2019)

$$I_L = I_{ph} - I_{sd1} \left[\exp \left(\frac{q(V_L + I_L R_s)}{a_1 V_t} \right) - 1 \right] - I_{sd2} \left[\exp \left(\frac{q(V_L + I_L R_s)}{a_2 V_t} \right) - 1 \right] - I_{sd3} \left[\exp \left(\frac{q(V_L + I_L R_s)}{a_3 V_t} \right) - 1 \right] - \frac{V_L + I_L R_s}{R_{sh}} \quad (5)$$

where a_3 denotes ideality factor of the third diode.

Therefore, I_{ph} , I_{sd1} , I_{sd2} , I_{sd3} , R_s , R_{sh} , a_1 , a_2 and a_3 are nine data that TDM needs to identify.

TABLE 1 Error functions of DDM and TDM.

Model	Error function	Solution vector
DDM	$f_{\text{DDM}}(V_L, I_L, x) = I_{\text{ph}} - I_{\text{sd1}} [\exp(\frac{q(V_i + I_L R_s)}{a_1 V_i}) - 1] - I_{\text{sd2}} [\exp(\frac{q(V_i + I_L R_s)}{a_2 V_i}) - 1] - \frac{V_i + I_L R_s}{R_{\text{sh}}} - I_L$	$x = \{I_{\text{ph}}, I_{\text{sd1}}, I_{\text{sd2}}, R_s, R_{\text{sh}}, a_1, a_2\}$
TDM	$f_{\text{TDM}}(V_L, I_L, x) = I_{\text{ph}} - I_{\text{sd1}} [\exp(\frac{q(V_i + I_L R_s)}{a_1 V_i}) - 1] - I_{\text{sd2}} [\exp(\frac{q(V_i + I_L R_s)}{a_2 V_i}) - 1] - I_{\text{sd3}} [\exp(\frac{q(V_i + I_L R_s)}{a_3 V_i}) - 1] - \frac{V_i + I_L R_s}{R_{\text{sh}}} - I_L$	$x = \{I_{\text{ph}}, I_{\text{sd1}}, I_{\text{sd2}}, I_{\text{sd3}}, R_s, R_{\text{sh}}, a_1, a_2, a_3\}$

Objective function

In order to implement an exercise to efficiently minimize the error between experimental and simulated data, a parameter extraction technique is used to determine the optimal parameters for the PV model, which can be quantitatively evaluated with the assistance of an objective function. Here, the root mean square error (RMSE) is taken as the objective function, as follows:

$$\text{RMSE}(x) = \sqrt{\frac{1}{N} \sum_{k=1}^N (f(V_L, I_L, x))^2} \quad (6)$$

where x represents the parameter vector to be identified, and N represents the number of experimental data.

In order to make the experimental data results more convincing, different error functions are given in Table 1.

Based on Table 1, for the sake of minimizing the error between experimental data and simulated data, objective function $\text{RMSE}(x)$ needs to be minimized by optimizing solution vector x . Note that objective function value is inversely proportional to the solution quality.

Peafowl optimization algorithm

POA is based on the courtship, foraging and chasing behaviors of green peafowls (Wang et al., 2022). On this basis, a general mathematical model is established. Male peacocks have delicate feathers to show their unique position advantage in the population. Male peacocks usually take the initiative to attract female peahens after finding high-quality food, and then seek mating. The more beautiful a male peacock's tail is, the more females it attracts by strutting and shaking its feathers. Once the male peacock finds food, they will not only open their feathers, but also further dance to expand the area to attract females (Wang et al., 2022). The dance mode can be divided into two types: rotating in place and walking in circles. Male peacocks also make cat like noises to attract female peahens. Male peacocks are polygamous, so they want to attract as many female peacocks as possible and mate with them.

The next aims to illustrate the main optimization mechanisms and principles of POA, to further demonstrate the superiority of this method. In order to more concisely introduce the core optimization principle of POA, only the core mechanisms are illustrated. More details can be referred to literature (Wang et al., 2022) for interested readers for more in-depth learning.

Courtship behavior of peacocks

When the peacock is in the mating season, the male peacock will hover near the food source through three behaviors: tail-spreading, rotating and flapping. There are two rotation modes around the food source, and the mechanism of these two rotation modes is dependent on the fitness function value. In particular, when the value of the fitness function is larger, the radius of the peacock's rotation around the food is smaller, but the probability of the peacock's rotation around the food is higher. The peacock with worse fitness function has a larger rotation radius, and this mathematical model is described as

$$X_{\text{Pc1}} = X_{\text{Pc1}}(t) + 1 \cdot R_s \cdot \frac{X_{r1}}{\|X_{r1}\|} \quad (7)$$

$$X_{\text{Pc2}} = \begin{cases} X_{\text{Pc2}}(t) + 1.5 \cdot R_s \cdot \frac{X_{r2}}{\|X_{r2}\|}, & r_1 < 0.9 \\ X_{\text{Pc2}}(t), & \text{otherwise} \end{cases} \quad (8)$$

$$X_{\text{Pc3}} = \begin{cases} X_{\text{Pc3}}(t) + 2 \cdot R_s \cdot \frac{X_{r3}}{\|X_{r3}\|}, & r_2 < 0.8 \\ X_{\text{Pc3}}(t), & \text{otherwise} \end{cases} \quad (9)$$

$$X_{\text{Pc4}} = \begin{cases} X_{\text{Pc4}}(t) + 3 \cdot R_s \cdot \frac{X_{r4}}{\|X_{r4}\|}, & r_3 < 0.6 \\ X_{\text{Pc4}}(t), & \text{otherwise} \end{cases} \quad (10)$$

$$X_{\text{Pc5}} = \begin{cases} X_{\text{Pc5}}(t) + 5 \cdot R_s \cdot \frac{X_{r5}}{\|X_{r5}\|}, & r_4 < 0.3 \\ X_{\text{Pc5}}(t), & \text{otherwise} \end{cases} \quad (11)$$

$$X_r = 2 \cdot \text{rand}(1, \text{Dim}) - 1 \quad (12)$$

where X_{Pci} represents the position vector of the i th male peacock; R_s represents the rotation radius of the circle; X_r represents random vector; $\|X_r\|$ is the modulus of X_r ; r_1, r_2, r_3, r_4 represent the four random numbers of $[0, 1]$.

Approaching behavior of peahens

Peacocks constantly adjust their behavior during courtship, adopting approach mechanisms and adaptive search mechanisms. In the process of courtship, the female peacock first approaches the male peacock and will look around. Therefore, the fitness of mutual attraction between male and female peacocks is proportional. The mathematical model of this process is as follows (Wang et al., 2022):

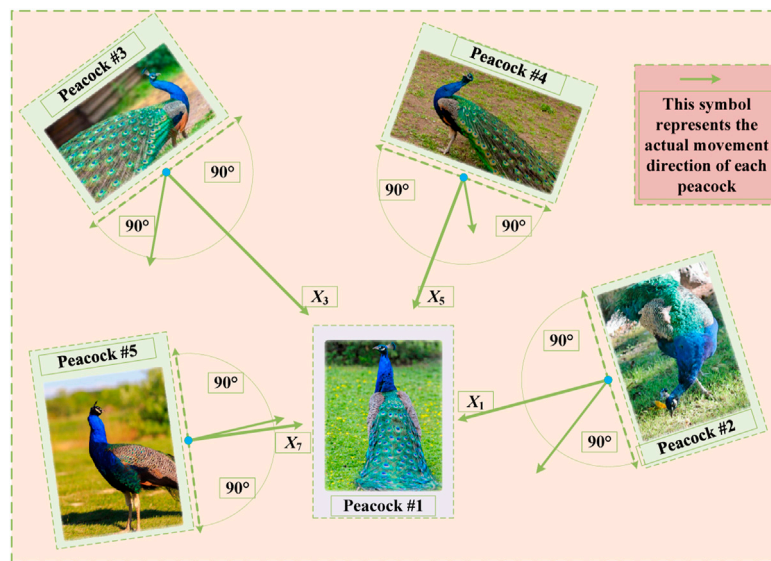


FIGURE 3
Interaction mechanism among different peacocks.

$$X_{Ph} = \begin{cases} X_{Ph}(t) + 3 \cdot \theta \cdot (X_{Pc1} - X_{Ph}(t)), & 0.6 \leq r_5 \leq 1 \\ X_{Ph}(t) + 3 \cdot \theta \cdot (X_{Pc2} - X_{Ph}(t)), & 0.4 \leq r_5 < 0.6 \\ X_{Ph}(t) + 3 \cdot \theta \cdot (X_{Pc3} - X_{Ph}(t)), & 0.2 \leq r_5 < 0.4 \\ X_{Ph}(t) + 3 \cdot \theta \cdot (X_{Pc4} - X_{Ph}(t)), & 0.1 \leq r_5 < 0.2 \\ X_{Ph}(t) + 3 \cdot \theta \cdot (X_{Pc5} - X_{Ph}(t)), & 0 \leq r_5 < 0.1 \end{cases} \quad (13)$$

$$\theta = \theta_0 + \theta_1 - \theta_0 \cdot \frac{t}{t_{\max}} \quad (14)$$

where r_5 is defined as a random number in $[0,1]$; while θ_0 is assigned a value of 0.1 and θ_1 is assigned a value of 1.

Random food searching behavior of peafowl cubs

In order to play a random search role in the food search space, juvenile peacocks will actively approach male peacocks with good food sources (the highest fitness). In this paper, one of the five peacocks is used as the target object. These five peacocks guide the juvenile peacocks with equal probability. In this process, the random search behavior of the peacocks is described by the Levy flight, and the behavior of peafowl cub can be expressed as

$$X_{SPc} = \begin{cases} X_{Pc1}(t), & 0.8 < r_8 \leq 1 \\ X_{Pc2}(t), & 0.6 < r_8 \leq 0.8 \\ X_{Pc3}(t), & 0.4 < r_8 \leq 0.6 \\ X_{Pc4}(t), & 0.2 < r_8 \leq 0.4 \\ X_{Pc5}(t), & 0 \leq r_8 \leq 0.2 \end{cases} \quad (15)$$

$$X_{PcC} = X_{PcC}(t) + \alpha \cdot \text{Levy} \cdot (X_{Pc1}(t) - X_{PcC}(t)) + \delta \cdot (X_{SPc} - X_{PcC}(t)) \quad (16)$$

where r_8 represents a random number on $[0, 1]$; X_{SPc} is defined as the position vector of the peacock, X_{PcC} refers to the position vector of the juvenile peacock; α and δ are expressed as coefficient factors.

Besides, the five peacocks also have the internal interactions among them. In addition, male peacock #1 has the best food source, the remaining four male peacocks will gradually move towards male peacock #1. The detailed pattern can be shown in Figure 3.

The optimization framework of PV cell parameter identification based on POA is shown in Figure 4. The historical data of the output voltage and current determined by the PV cell will be regarded as the input of the POA and converted into the objective function. According to the specific PV cell model, the optimization program is executed based on POA, and finally the identification parameters of PV cells are output.

Case studies

In this section, two different kinds of PV models, i.e., DDM and TDM are adopted for parameter identification based on POA. The experimental I - V data utilized for simulation are extracted from a 57 mm diameter R.T.C. France solar cell under the weather condition ($G = 1000 \text{ W/m}^2$ and $T = 33^\circ\text{C}$). Note that there are in total of 26 sets of I - V data.

POA is in comparison with other two meta-heuristic algorithms, e.g., ABC (Oliva et al., 2014) and WOA (Xiong et al., 2018).

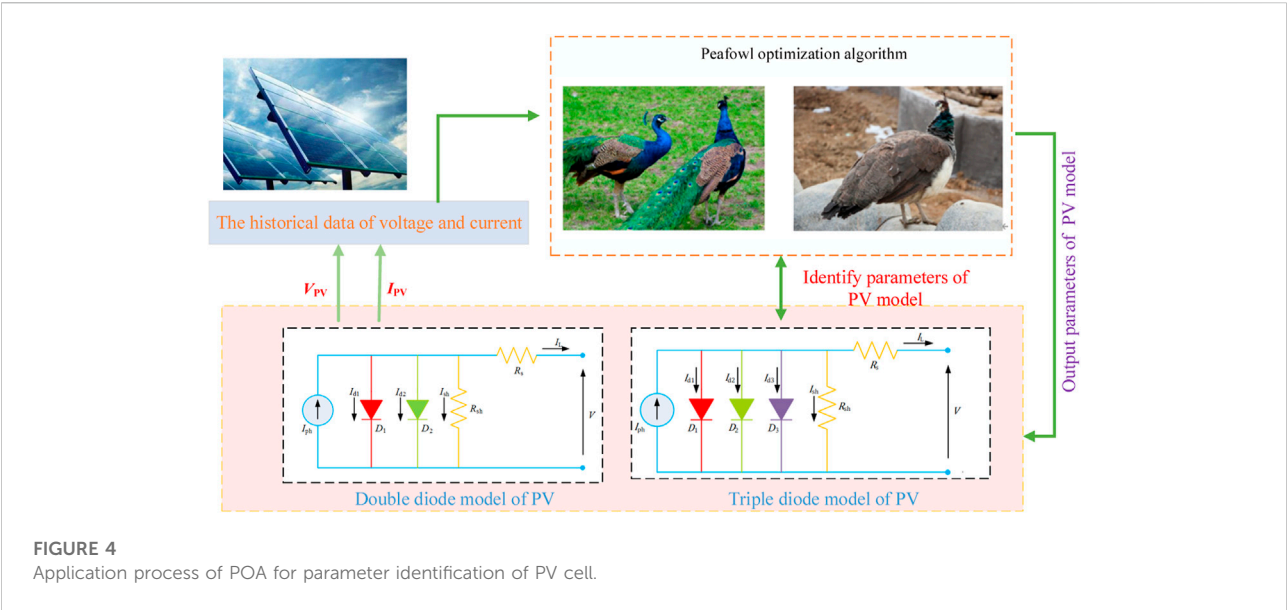


FIGURE 4 Application process of POA for parameter identification of PV cell.

TABLE 2 Parameters identification results under DDM.

Algorithm	I_{ph} (A)	I_{01} (μ A)	R_s (Ω)	R_{sh} (Ω)	a_1	I_{02} (μ A)	a_2	RMSE
ABC	0.7604	0.5450	0.0372	52.0978	1.8104	0.1511	1.4196	1.1915E-03
WOA	0.7603	0.5333	0.0358	71.7116	1.6921	0.1502	1.4360	1.1342E-03
POA	0.7608	0.2366	0.0367	53.4175	1.4570	0.2602	1.7944	9.8602E-04

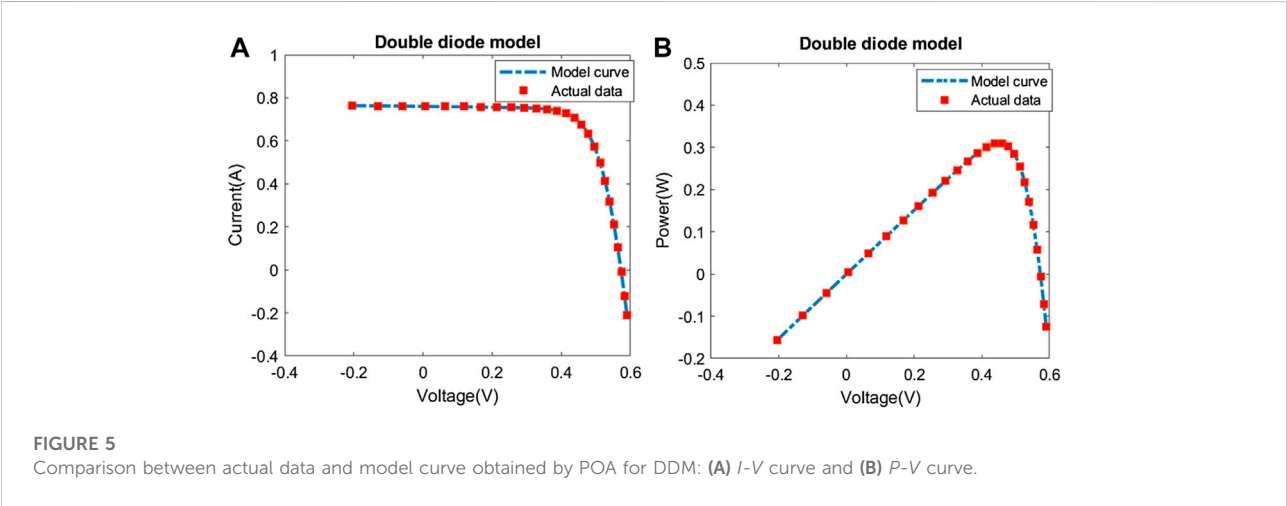


FIGURE 5 Comparison between actual data and model curve obtained by POA for DDM: (A) *I*-*V* curve and (B) *P*-*V* curve.

Particularly, their maximum iteration number is designed to be the same, i.e., 200, while all approaches are executed in 30 independent runs to acquire statistical results. Besides, population size of each algorithm is designed to be 50 and 70 for DDM and TDM,

respectively. Note that the best simulation results of all the methods are highlighted in bold. All case studies are undertaken by Matlab 2021a through a personal computer with IntelR CoreTMi7 CPU at 2.0 GHz and 32 GB of RAM.

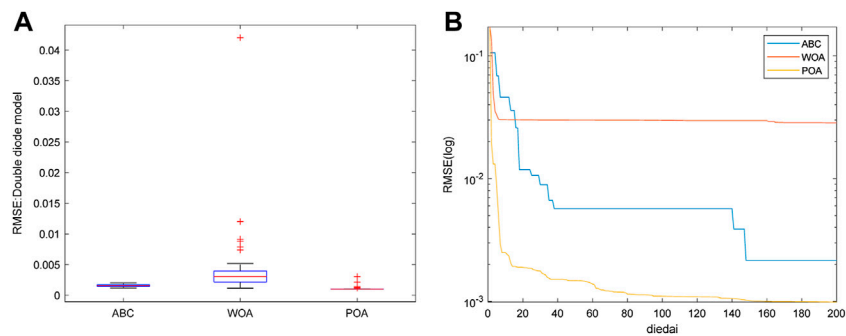


FIGURE 6
Boxplot graph and convergence curve obtained by POA for DDM: **(A)** boxplot graph and **(B)** convergence curve.

TABLE 3 Model parameters identified by various algorithms for TDM.

Algorithm	I_{ph} (A)	I_{01} (μ A)	R_s (Ω)	R_{sh} (Ω)	a_1	I_{02} (μ A)	a_2	I_{03} (μ A)	a_3	RMSE
ABC	0.7615	0.2446	0.0364	44.8763	1.4618	0.3504	1.5620	0.2663	1.9265	1.1656E-03
WOA	0.7598	0.3709	0.0364	76.7663	1.5757	0.0289	1.8577	0.0779	1.4071	1.2060E-03
POA	0.7607	0.0739	0.0363	55.5735	1.9996	0.2745	1.4795	0.2265	1.9685	9.8462E-04

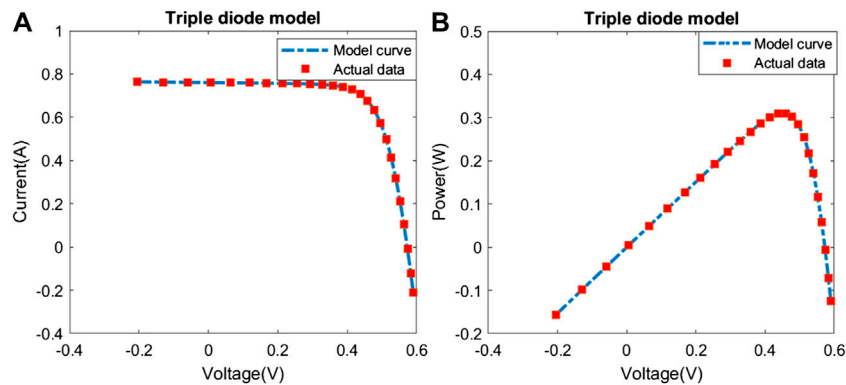


FIGURE 7
Comparison between actual data and model curve obtained by POA for TDM: **(A)** I - V curve and **(B)** P - V curve.

Results discussion on double diode model

The optimal parameters and RMSE obtained by different algorithms are demonstrated in Table 2, among them the best result is highlighted in bold. Based on Table 2, it can be seen that POA can achieve the most satisfactory performance compared against its competitors in terms of accuracy. The RMSE obtained by POA is only 51.19% and 86.93% to that of ABC and WOA, respectively.

Figure 5 illustrate the I - V curve and P - V curve fitting results obtained by POA under DDM, which indicates that the identified results are highly matched with the real data. Thus, the model parameters identification accuracy of POA can be further improved.

Besides, the boxplot graph and convergence curves obtained by various algorithm are respectively shown in Figures 6A,B. Boxplot graph shows that the distribution range of POA is the

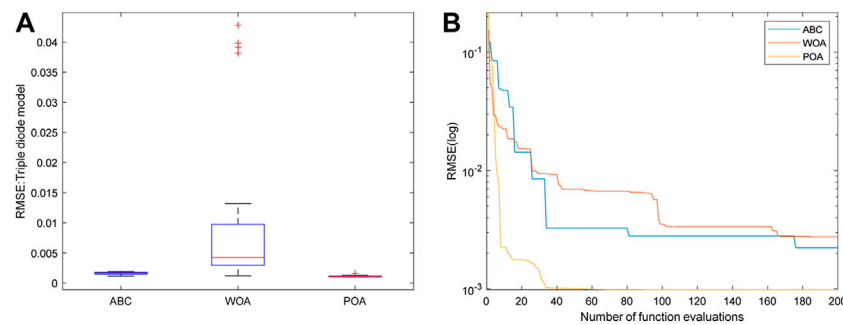


FIGURE 8

Boxplot graph and convergence curve obtained by POA for TDM: (A) boxplot graph and (B) convergence curve.

smallest among all the algorithms with the minimal lower and upper bounds, which indicates that POA can acquire the lowest RMSE with the highest stability. Convergence curves show that POA owns the highest convergence speed and stability.

Results discussion on three-diode model

Table 3 shows the simulation results obtained by POA for TDM parameter estimation, in which the most accurate results along with its corresponding algorithm are highlighted in bold. Thus, it can be observed that POA can realize the highest quality estimation performance compared with ABC and WOA. The RMSE obtained by POA is only 84.47% and 81.64% to that of ABC and WOA, respectively.

The output I - V curve and P - V curve for TDM obtained by POA is shown in Figure 7, upon which it can be illustrated that the simulated data is extremely similar to the real data, which can effectively verify the parameters identification reliability of POA.

Furthermore, the boxplot graph and convergence curves of different algorithms are demonstrated in Figures 8A,B, respectively. Figure 8A shows that POA can obtain the smallest distribution range with the minimal lower and upper bounds, which can validate the high identification accuracy and stability of POA. From Figure 8B, it shows that POA can search the global optimum in a high convergence rate.

Conclusion

In this paper, the core component of the PV power generation system, namely the PV cell, is taken as the research object. The purpose of this paper is to accurately and

effectively identify the unknown parameters in its model, so as to achieve its accurate modeling, so as to better guide the later optimal power generation and operation control. The main contributions of this paper are summarized as follows:

- Through the study of peacock behavior, I received relevant inspiration and used peacock behavior as a search mechanism. In this paper, a novel POA optimization algorithm is proposed. For the parameter identification problem of photovoltaic model, this algorithm is used to optimize the identification results, thereby improving the accuracy of photovoltaic cell parameter identification;
- The novelty of POA algorithm is that the algorithm includes efficient search operators and heuristics, in order to avoid getting trapped in local optima during the search process. The algorithm can dynamically adjust the optimization mechanism to find a balance between local search and global search, so as to improve the convergence accuracy of parameter identification;
- The algorithm is applied to the parameter identification of DDM and TDM PV cell models, and the effectiveness and reliability of POA for PV cell parameter identification are comprehensively verified. Case studies show that POA can effectively improve the accuracy and stability of parameter identification compared with other algorithms.

Further studies can be focused on the improvement and modification on the algorithm structure to lower the parameter tuning burden. Also, more different PV cell models can be applied for more comprehensive validation under more complex operation conditions, which is more beneficial for engineering applications.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YZ: Conceptualization, Writing—Original Draft; EZ: Formal analysis, Software, Supervision; PA: Project administration, Resources, Writing—Review and; Editing.

Funding

The work was supported by Ningbo Natural Science Foundation 2019A610106 and the Open Research Project of the State Key Laboratory of Industrial Control Technology, Zhejiang University, China (No. ICT2022B66).

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Conflict of interest

EZ was employed by the Ningbo Jianan Electronics Company Limited.

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 17 June 2022
ACCEPTED 15 July 2022
PUBLISHED 23 August 2022

CITATION
Zhou J, Liu C and Li K (2022), PV array
reconfiguration with electrical energy
storage system for power system
frequency regulation.
Front. Energy Res. 10:971628.
doi: 10.3389/fenrg.2022.971628

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PV array reconfiguration with electrical energy storage system for power system frequency regulation

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In this work, a novel PV station participating FR technique based on PV array reconfiguration and battery energy storage system (BESS) is put forward. Through the PV array reconfiguration under Partial shading condition, photovoltaic (PV) system can adjust the output power according to the power dispatch instruction. And with the help of BESS, The PV station can achieve continuous power output. Specifically, a joint PV energy storage system model combining profit maximization and power deviation minimization is established. In order to two conflicting goals simultaneously, multi-objective golden eagle optimizer and improved ideal point decision making method are applied. And Lagrange function is given to determine the weight coefficients of each objective more fairly. Two cases are designed and tested. In the high frequency response simulation test, the profit is increased by 8.4% and the power deviation from FR signal is decreased by 19.98%; meanwhile the profit is increased by 10.07% and power deviation is decreased by 67.69% in the low frequency response test. Therefore, the simulation results verify that the proposed method contributes to the frequency response of PV station.

KEYWORDS

PV array reconfiguration, battery energy storage system, frequency regulation, multi-objective golden eagle optimizer, optimizing operation

Introduction

With the increasing severity of environmental problems and the consumption of fossil fuels, solar energy has become one of the most widely used renewable energy sources due to its huge reserves, clean and environmentally friendly (Yang et al., 2021). Driven by the national strategy of “carbon neutral, emission peak”, the proportion of Photovoltaic (PV) power generation in the power system will continue to grow (Yang et al., 2021) (Kaushika and Gautam, 2003). In the context of high proportion of renewable energy in new power system, the traditional frequency regulation (FR) control means are stretched, as a result PV system participating in power grid FR is inevitable (Sai Krishna and Moger, 2019). Therefore, the research on the FR strategy based on PV reconfiguration coordinated with energy storage carried out in this work has important value for the frequency safety of the new power system.

Partial shading condition (PSC) (Laudani et al., 2018), (Ajmal et al., 2020) is one of the most common environmental factors which effecting the PV power generation efficiency and maximum power point tracking (MPPT) efficiency. Changing the connection topology of PV modules can equivalently disperse the originally concentrated shadows to the entire array, so as to reduce the influence of PSC and improve the output power (Rani et al., 2013). In recent years, researchers have developed a variety of PV array reconfiguration methods, mainly divided into two categories: static and dynamic.

The literature (NamaniRakesh and Madhavaram, 2016) studies the performance of three different topologies (parallel, total-cross-tied (TCT) and bridge structure) of PV array in PSC proposes that TCT topology extract the maximum power of the array. Sudoku scheme is used to reconfigures PV modules in literature (Horoufiany and Ghandehari, 2018). Literature (Shams El-Dein et al., 2013) introduces mathematical formulas based on mixed integer quadratic programming to disperse the shadow of TCT-connected PV arrays. In addition, static technique is a one-time reconfiguration method which can hardly settle time-varying shadow.

However, dynamic reconfiguration can adjust the switch matrix in real time according to the shadow change, so as to achieve the purpose of dynamically changing the electrical topological structure of the array (Deshkar et al., 2015), (Balraj and Stonier, 2020). The literature (Sanseverino et al., 2015) proposes a PV array reconfiguration method based on knapsack problem, and uses additional unshaded PV components to compensate for components that are heavily shaded. In recent years, the application of meta-heuristic algorithms to PV array reconfiguration has become a new trend, such as genetic algorithm (Deshkar et al., 2015), particle swarm optimization (Babu et al., 2018), and grasshopper optimization algorithms (Fathy, 2018), butterfly optimization algorithm (Fathy, 2020) and artificial ecological optimization algorithm (Yousri et al., 2020a).

None of the current PV reconfiguration studies have taken the application of PV reconfiguration techniques to grid frequency regulation into account (Zhang et al., 2021), so this work proposes a PV array reconfiguration of grid frequency regulation strategy based on multi-objective golden eagle optimizer (MOGEO) (Mohammadi-Balani et al., 2021) which has strong global exploration ability and optimization stability. At the same time, the battery energy storage system (BESS) is introduced to coordinate the PV system so that the reconfiguration can achieve linear continuity response to FR instructions (Yousri et al., 2020b) (González-Castaño et al., 2021).

From the view of PV power station, the PV system and BESS are considered to participate frequency regulation at the same time, to provide ancillary services (Krishnan et al., 2020), (Bi et al., 2020). According to the electric price, operation cost, the PV array reconfiguration optimization economic model is established to determine the required energy storage power, power generation

planning and charging and discharging strategy of PV power plant under different shadows and frequency regulation capacity, so as to maximize the joint PV energy storage system. Leave out the dynamic interaction with the system frequency, the system frequency is regarded as the known input of the model, so the final model can be solved by heuristic algorithm.

Design of multi-objective golden eagle optimizer

Spiral movement and prey selection

Each golden eagle can remember its best prey and cruises around its own prey or others' preys. Prey selection strategies play an important role in MOGEO. For the sake of enhancing the exploration efficiency of agents, a one-to-one mapping program is proposed in MOGEO so that each prey can be randomly assigned to only one golden eagle. And then every golden eagle cruises and attacks the chosen prey. And the schematic diagram of one-to-one mapping program is shown in Figure 1.

Exploitation and exploration

The golden eagle's attack behavior can be viewed as a vector. The starting point of this vector is the current position of the golden eagle and the destination is the prey. So, the attack vector which emphasizes the development stage in MOGEO of agent i can be modeled by Formula (1).

$$\vec{A}_i = \vec{X}_f^* - \vec{X}_i \quad (1)$$

where, $\vec{X}_f^*$ denotes the position of prey; and $\vec{X}_i$ represents the position of the eagle i in current iteration.

The speed direction of cruising vector is perpendicular to the attack vector. The cruising vector can be obtained only when the equation of the tangent hyperplane is calculated. Hence the expression of the n -dimensional hyperplane can be calculated by Eq. 2.

$$h_1x_1 + h_2x_2 + \dots + h_nx_n = d \Rightarrow \sum_{j=1}^n h_jx_j = d \quad (2)$$

The steps of golden eagle randomly seeking the destination position C located on a n -dimensional cruising hyperplane are as follows:

Step 1 A variable is randomly selected to assigned as the fixed variable from whole variable set other than whose corresponding attack vector is 0.

Step 2 Except for the p th variable whose value is fixed, appoints random figures to all variables.

Step 3 Use Eq. 3 to acquire the value of the fixed parameter.

$$c_k = \frac{d - \sum_{i,j \neq p} a_j}{a_p} \quad (3)$$

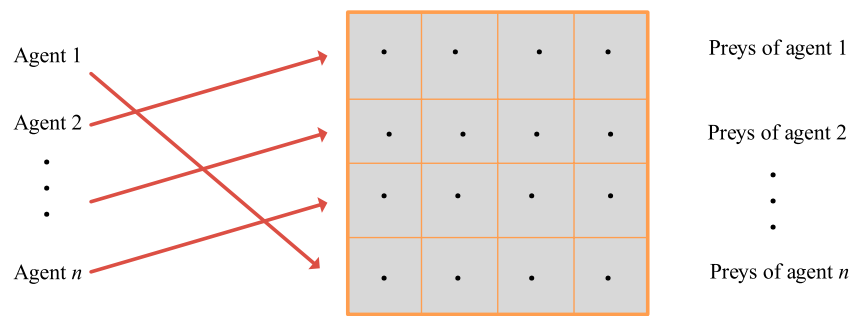


FIGURE 1
One-to-one mapping in MOGEO prey selection.

where, c_k is the p th member of destination position C ; a_j denotes the j th member in the vector set $\vec{A}_i$; d represents the distance.

Updating of location

The position movement of the golden eagle consists of two parts, attack and cruise, which affect and restrict each other, as shown in the following equation.

$$\begin{cases} \Delta x_i = r_1 p_a \frac{\vec{A}_i}{\|\vec{A}_i\|} + r_2 p_c \frac{\vec{C}_i}{\|\vec{C}_i\|} \\ x(t+1) = x(t) + \Delta x_i(t) \end{cases} \quad (4)$$

where, p_a and p_c are attack and cruise coefficient respectively, whose computing method can refer to original MOGEO research paper; these two coefficients adjust the attack or cruise tendency of golden eagle; r_1 and r_2 are random vectors, respectively; and $\vec{A}_i$ represents the attack vector; $\vec{C}_i$ indicates cruising vector; $x(t+1)$ denotes the position of agent in the $(t+1)$ iteration.

When the new position of the golden eagle is better than the original position, the original position is replaced by the new coordinates; Instead, keep the original position. In the next iteration, compute the new attack vector and cruise vector, and move to the new position. Iteration is not stopped until the loop termination condition is met.

Mathematical modeling of combined photovoltaic energy storage system revenue

Modeling of total-cross-tied structure photovoltaic arrays

Many individual PV cells form a PV module, and multiple PV modules form a PV array by series and parallel connection,

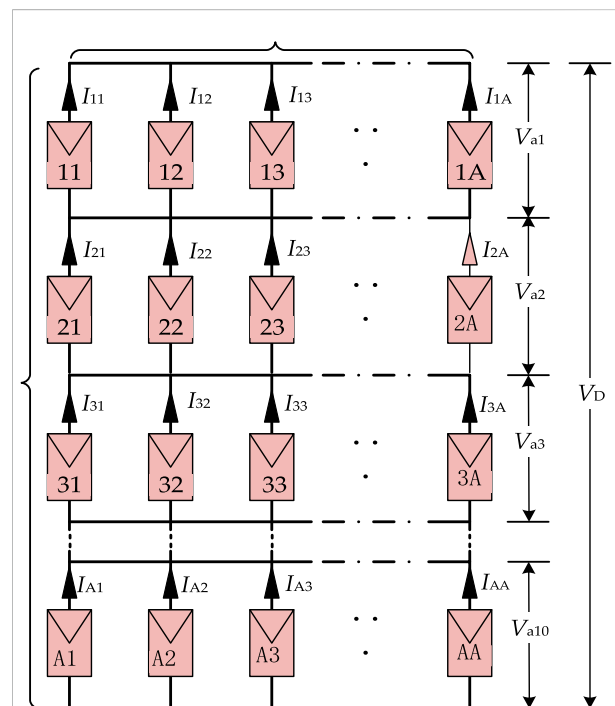


FIGURE 2
One 10 × 10 TCT connected array in a PV power plant.

and correspondingly, multiple PV arrays can form a PV system. For ease of study, the PV cell can be seen as a current generator. According to the general model of PV cell, the current of PV cell can be expressed as below:

$$I_{\text{cell}} = I_{\text{Light}} - I_d - I_{\text{sh}} \quad (5)$$

where I_{cell} represents the output current of the PV cell, I_{Light} denotes the photo-generated current; I_d is the current of diode; I_p represents the current of parallel resistance.

Since the TCT topology is less affected by shadows under PSC, the output power is more stable, which is widely used in the

study of PV arrays. A 10×10 scale TCT structured PV array is shown in Figure 2, each of which is connected in parallel by 9 PV modules, and then such 9 lines are connected in series by Kirchhoff's voltage law (KVL) and KCL provide output voltage and current for the entire PV array:

$$V_D = \sum_{p=1}^{10} V_{ap} \quad (6)$$

$$I_D = \sum_{q=0}^{10} (I_{pq} - I_{(p+1)q}) = 0, \quad p = 0, 1, 2, \dots, 9 \quad (7)$$

where V_D is the output voltage of the array, V_{ap} represents the row voltage of p th row, and I_D means the total output current, I_{pq} indicates the output current of the PV module in q th column and p th row.

Constraints

1) Constraints of battery.

In order to ensure the safe operation and life of the battery, it is necessary to constrain its charge and discharge power and the remaining capacity of the battery, as shown below:

$$P_{\text{bess}}^{\min} \leq P_{\text{bess}}(t) \leq P_{\text{bess}}^{\max}, \quad t \in T \quad (8)$$

$$\text{SOC}_{\text{bess}}^{\min} \cdot E_{\text{bess}} \leq E_{\text{bess}}(t) \leq \text{SOC}_{\text{bess}}^{\max} \cdot E_{\text{bess}}, \quad t \in T \quad (9)$$

$$\text{SOC}_{\text{bess}}(t) = \begin{cases} \text{SOC}_{\text{bess}}(t-1) + P_{\text{bess}}(t) \cdot \Delta t \cdot \eta_{\text{ch}} / E_{\text{bess}}, & \text{if } P_{\text{bess}}(t) \geq 0 \\ \text{SOC}_{\text{bess}}(t-1) + P_{\text{bess}}(t) \cdot \Delta t / (\eta_{\text{dis}} \cdot E_{\text{bess}}), & \text{otherwise} \end{cases} \quad (10)$$

Where, $P_{\text{bess}}^{\max}$, $P_{\text{bess}}^{\min}$ are the maximum and minimum charging power of BESS, respectively. $\text{SOC}_{\text{bess}}^{\max}$ and $\text{SOC}_{\text{bess}}^{\min}$ severally represent the maximum and minimum state of charge (SOC) of BESS; η_{ch} and η_{dis} are the charging and discharging efficiency; Δt denotes the control period; and E_{bess} means the rated capacity of BESS.

2) Balance constraint of frequency regulation power.

The power responded to high frequency and low frequency from joint PV energy storage system is provided by PV array and energy storage systems together, which can be expressed as follows:

$$P_{\text{fr}}^+(t) = PV_{\text{fr}}^+(t) + E_{\text{b,fr}}^+(t) / \eta_{\text{ch}} \quad (11)$$

$$P_{\text{fr}}^-(t) = PV_{\text{fr}}^-(t) + E_{\text{b,fr}}^-(t) / \eta_{\text{dis}} \quad (12)$$

where, $PV_{\text{fr}}^+(t)$ and $PV_{\text{fr}}^-(t)$ are the decreased power generation for higher system frequency and the increased power generation for lower system frequency; the sum of $P_{\text{fr}}^+(t)$ and $P_{\text{fr}}^-(t)$ is the total frequency regulation power.

3) Full response constraint of frequency regulation power.

As the frequency response is the mandatory auxiliary service of the power system, the frequency regulation power provided by

combined PV energy storage system must be satisfied with the frequency regulation capacity calculated according to the grid-connection guidelines requirements.

$$P_{\text{fr}}(t) = P_{\text{req}}(t) \quad (13)$$

where, $P_{\text{req}}(t)$ is the required frequency modulation capacity calculated by the grid-connected guidelines in time period t , which is related to the percentage of the current output in the installed PV power station.

4) Constraints of PV power sale.

$$P_g(t) = P_{\text{pv}}(t) - P_{\text{fr}}^+(t) + P_{\text{fr}}^-(t) \quad (14)$$

where, $P_g(t)$ is power sale quantity in electric quantity market; $P_{\text{pv}}(t)$ denotes the maximum power generation of PV array which is depending on the sunlight conditions. This constraint reflects that in the power market, the electricity sale in the conventional market and the frequency regulation electricity participating in the auxiliary service are calculated separately.

Objective function

In order to increase the power generation income of the PV storage power station and make the power response to the FM signal at the same time, two conflicting goals are considered in this paper, the first goal is to minimize the average power deviation between the power output of the PV array coordinated energy storage battery and the FR signal f_1 . The second is to maximize the power generation revenue of the PV storage power station f_2 , which is equivalent to the difference between the electricity sales revenue of PV power generation and the operating cost of energy storage batteries. In the electric power market, the electric quantity market and the auxiliary service market are generally separated, so the two parts of electric quantity are charged separately in calculation, and both of them are regarded as the income of the optical storage combined system in the market. In summary, the objective function proposed in this article can be defined as follows:

$$\begin{cases} \min f_1 = \frac{1}{T} \sum_{t \in T} |P_{\text{FR}}(t) - [P_{\text{pv}}(t) - P_{\text{bess}}(t)]| \\ \max f_2 = \lambda_1 \cdot \sum_{t \in T} [P_{\text{pv}}(t) - P_{\text{bess}}(t)] + C_p + M_p - C_{\text{bess}} \end{cases} \quad (15)$$

Where, T (ΔT) represents the response to the FM time, $P_{\text{bess}}(t)$ is the charging power of energy storage, λ_1 is the conventional electricity price, C_p means the FM capacity compensation income, M_p indicates the FM mileage compensation income, C_{bess} denotes the cost of energy storage batteries.

$$C_p = \lambda_2 C \cdot A \quad (16)$$

where, λ_2 represents the capacity compensation standard; A is the AGC operation performance index, assigned 1; C means the

limited range capacity that the AGC can automatically adjust within 5 min during dispatch period, of which the upper limit is assigned the predicted output of the PV storage power station, and the lower limit is assigned 60% of the installed capacity of PV station.

$$M_p = \lambda_3 \sum_{t \in T} [P(t+1) - P(t)] \cdot A \quad (17)$$

where, λ_3 is the mileage compensation standard; the value of A is 1; $P(t)$ is the predicted output of the optical storage power station.

For the convenience of research, the cost of energy storage here only considers the charge and discharge cost of the battery during operation.

$$C_{\text{bess}} = \sum_{t \in T} [\Delta E_{\text{bess}}(t) \cdot \lambda_{\text{ch}}] \quad (18)$$

where, $\Delta E_{\text{bess}}(t)$ is the amount of energy change in the energy storage battery in the t th minute, λ_{ch} represents the unit cost of charge and discharge.

During the practical operation process of MOGEO, in order to fit the characteristics of the algorithm, it is necessary to appropriately adjust the objective function so that the fitness function of the algorithm program is calculated as follows:

$$\begin{cases} \min f'_1 = f_1 + \psi \cdot h \\ \min f'_2 = -f_2 + \psi \cdot h \end{cases} \quad (19)$$

where, ψ is the penalty factor which usually defined a large positive number; h is the number of violated constraints for Eqs 6–12; $Pe(t)$ reflects the constraints in the Eq. 7. The introduction of penalty function method can help to discard the incomprehension beyond the constraints. Specifically, the solution obtained during algorithm iterations will be retained to the next iteration if it is in the solution space. While the solution that violates the constraint is discarded.

Application design of photovoltaic reconfiguration solution based on pareto

The MOGEO proposed in this work is a multi-objective intelligent optimization algorithm, so the key problems including variable processing, fitness function, solution screening and compromise decision must be mainly solved in the model solution of joint PV energy storage system (Yousri et al., 2020c).

Variable processing and fitness function

PV array reconfiguration optimization and charge-discharge optimization of BESS contain both continuous and discrete variables (Mahmoud et al., 2019). Continuous variables can be

processed according to normal optimization; The discrete variables can be rounded by the values of the continuous space, and the upper and lower limits of the continuous optimization space are the upper and lower limits of the corresponding discrete variables (Horoufian and Ghandehari, 2017).

The fitness function of the algorithm must effectively combine the objective and constraint conditions of the proposed model, which can be performed by Eq. 17.

Storage and screening of pareto solutions

In the iteration process of MOGEO, the number of Pareto solutions will persistently grow. And the solutions will be put into a finite sized storeroom. The new non-dominant solution obtained by the MOGEO is compared with the non-dominant solution set in the storeroom. Based on the comparison result, the new non-dominant solution is determined whether to put in the storeroom or not. Like the general multi-objective optimization algorithm, the judgment process is divided into the following three situations.

- 1) If the new solution dominates one or more solutions in the storeroom, replace them with the new solution;
- 2) If the new solution is dominated by at least one solution in the storeroom, the new solution is discarded;
- 3) If the new solution does not have a dominant relationship with all the solutions in the storeroom, the new solution is added to the storage pool.

To improve the computing efficiency of the algorithm, the storeroom stores only a limited number of dynamic non-dominant solutions. Therefore, when the number of non-dominant solutions in the storeroom exceeds the threshold, redundant non-dominant solutions need to be removed. In order to screen out non-dominant solutions with crowded distribution, the algorithm removes them according to the number of adjacent solutions of each non-dominant solution. On the basis of obtaining the number of adjacent solutions of each non-dominant solution in the storeroom, the method of roulette is adopted to eliminate the non-dominant solutions whose adjacent solutions exceed the limit amount. The more the number of adjacent solutions of non-dominant solutions is, the greater the probability of being eliminated is.

Improved ideal point decision making method

According to the optimal Pareto front obtained by MOGEO, the target ideal point of the current optimization problem to be solved and the square of the Euclidean distance from each non-

TABLE 1 The procedure pseudocode of joint PV energy storage system reconfiguration.

- 1: Input: weather condition, frequency capacity demand, and electricity prices, etc.
- 2: Initialize the parameters of MOGEO and proposed model
- 3: Initialize the random solutions
- 4: Set $i = 1$
- 5: For $i \leq Itera_{max}$
- 6: Compute the fitness of all agents' through Eqs 17–21
- 7: Rank all the solutions, and calculate the number of adjacent solutions of each non-dominant solution in the storeroom
- 8: Update the non-dominated solution set based on the dominant relationship between the new solution and the solutions in storeroom
- 9: Update the position of the golden eagles based on Eqs 1–4
- 10: Update the solutions of all golden eagles
- 11: Set $i = i + 1$
- 12: End
- 13: Output: the Pareto front including PV array topology and charge/discharge power of BESS
- 14: Pick up the best compromise solution by improved ideal point decision making method given by Eqs 22–26

TABLE 2 Key parameters of the joint PV energy storage system.

Settings		Values
PV array	Amount of parallel-connected and series-connected PV module in a PV panel	10*5
	Rated power per PV module	200.039 W
	Scale of PV array	10 × 10
	Number of sub-systems	25
BESS	Maximum charging/discharging power of BESS	5 MW/h
	Minimum charging/discharging power of BESS	−5 MW/h
	Rated capacity of BESS	15 MWh
	Initial SOC of BESS	0.5
	Upper limit of SOC	0.2
	Lower limit of SOC	0.9
	Charge efficiency of BESS	0.95
	Discharge efficiency of BESS	0.95

TABLE 3 Input parameters of MOGEO.

λ_1	λ_2	λ_3	λ_{ch}	Maximum iterations	Size of population
800 ¥/MWh	5 ¥/MW	6 ¥/MW	1.37 ¥/MW	100	200

dominant solution to the ideal point can be computed. First, the objective function value of the non-dominant solution is normalized, as shown in the formula below.

$$y_j(i) = \frac{f'_j(i) - f'_{j,\min}(i)}{f'_{j,\max}(i) - f'_{j,\min}(i)}, \quad i = 1, 2 \quad (20)$$

where, $y_j(i)$ indicates the normalized value of objective function i of the j th non-dominant solution; $f'_{j,\min}$ and $f'_{j,\max}$ are minimum and maximum value of j th non-dominant solution.

Therefore, the ideal point of pareto frontier after normalization is (0, 0). So that the squared Euclidean distance from each nondominant solution to the ideal point is calculated by following formula.

$$D_j = \sum [y_j(i) - 0]^2 \rho(i)^2 \quad i = 1, 2 \quad (21)$$

where, D_j is squared Euclidean distance from the ideal point to the j th non-dominant solution; $\rho(i)$ denotes the weight coefficient of the i th objective function.

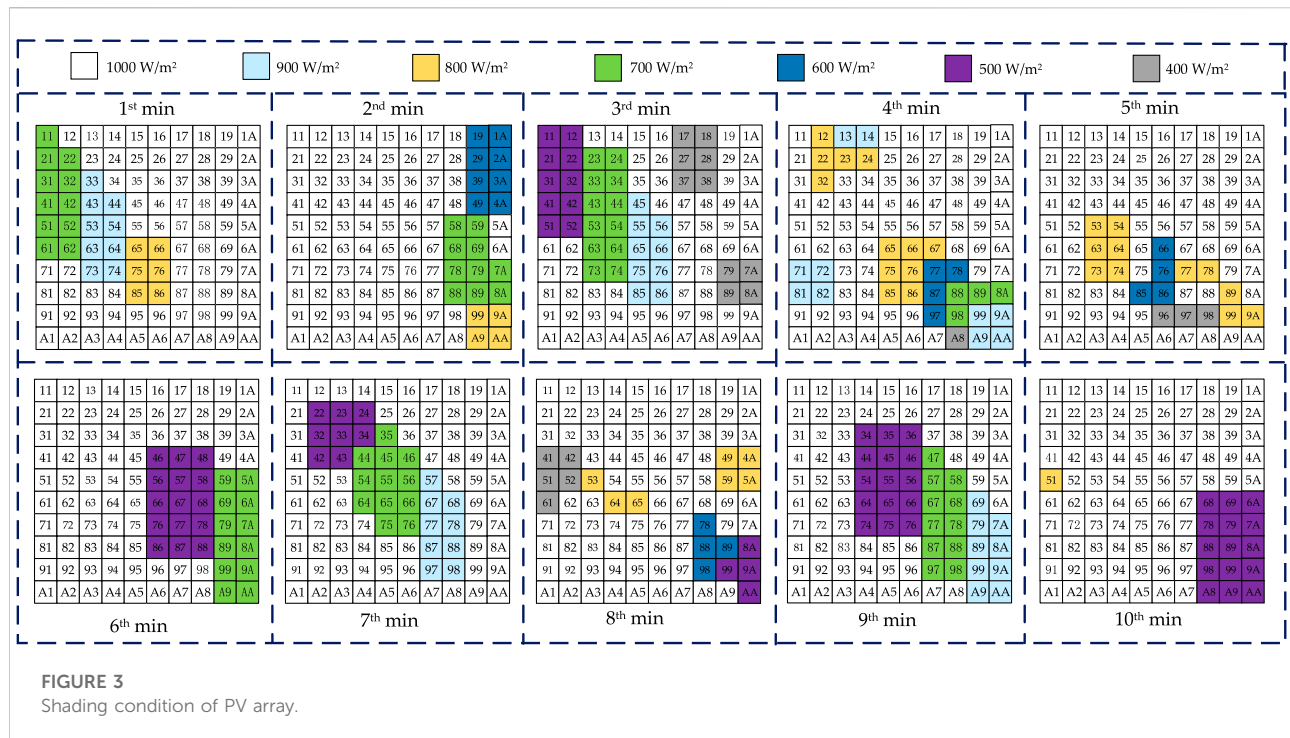


FIGURE 3
Shading condition of PV array.

The optimal weight model is constructed to give the weight coefficients of each objective more fairly, as shown in Eq. 20.

$$\begin{cases} \min Z = \sum_{j=1}^k D_j \\ \text{s.t. } \sum \rho(i) = 1, \quad \rho(i) > 0 \end{cases} \quad (22)$$

where, k is maximum number of non-dominant solution in the storeroom. By constructing the Lagrange function, the aforementioned optimal weight coefficients are obtained as below:

$$\rho(i) = \frac{1}{\sum_{j=1}^k \frac{1}{[y_j(i) - 0]^2} \cdot \sum [y_j(i) - 0]^2} \quad (23)$$

Hence, the decision compromise solution is determined by the following formula:

$$x_{\text{best}} = \arg \min_{j=1, 2, \dots, k} \sum [y_j(i) - 0]^2 \rho(i)^2 \quad (24)$$

In conclusion, the detailed steps of joint PV energy storage system participating frequency regulation is tabulated in Table 1.

Case studies

In order to verify the contribution of the joint PV energy storage system on improving the frequency condition of the grid based on proposed PV plant reconfiguration model, two simulation tests are designed and executed. In the studied

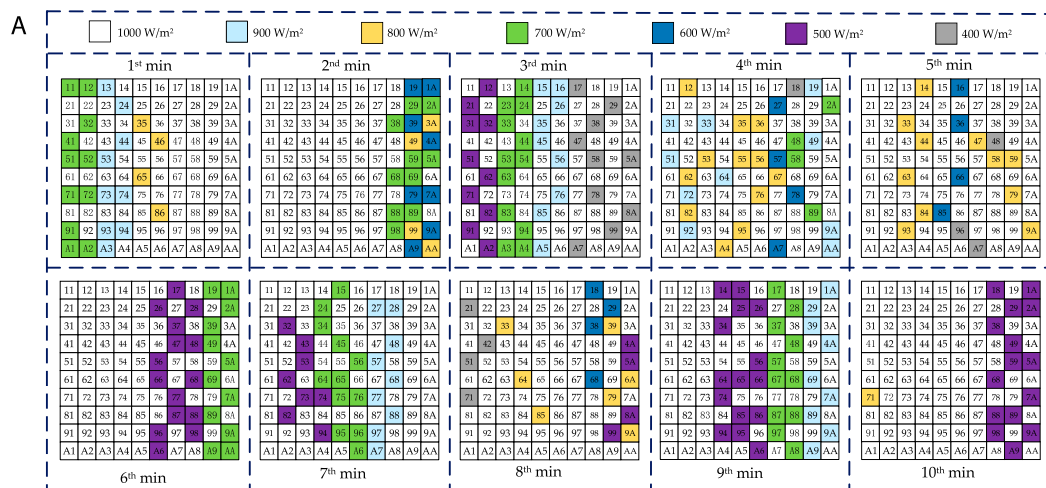
cases, the installed capacity of PV power station is 25 MW, and the capacity of BESS is 15 MW. Moreover, the key parameter settings of the joint PV energy storage system model are shown in Table 2.

The PV system consists of 25 subsystems, each of which is the same 10×10 PV array. In addition, the PV system is equipped with a 15 MW energy storage battery, which is used to cooperate with PV power generation, to alleviate the fluctuation of PV output, reduce the abandonment of sunlight, and realize better response to frequency regulation signal. As mentioned above, the joint PV energy storage system composed of PV system and BESS not only participates in the conventional electricity market, but also provides auxiliary services. Specifically, according to the operation rules of Yunnan Province frequency regulation auxiliary service market, the adopted parameters of auxiliary service compensation and input parameters of algorithm in the case studies are tabulated in Table 3.

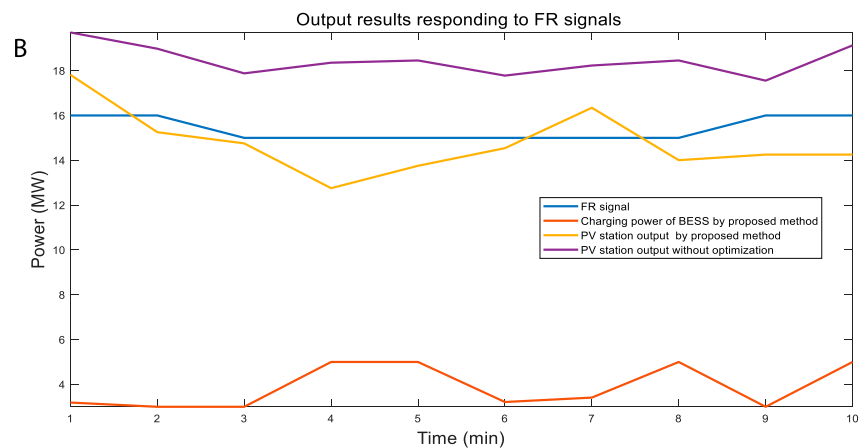
The shading which is varying with time of each subsystem is assumed same, and the shading condition of PV array in 10 minutes is depicted in Figure 3. Besides, all case studies are performed on Matlab R2019b.

Response to high frequency of grid

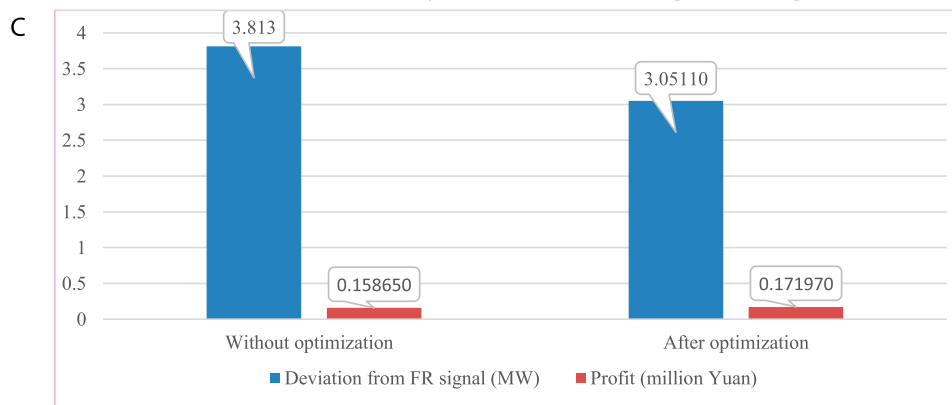
When the practical frequency of power grid is higher than power frequency, the joint PV energy storage system will receive



Shading distribution of PV array after reconfiguration.



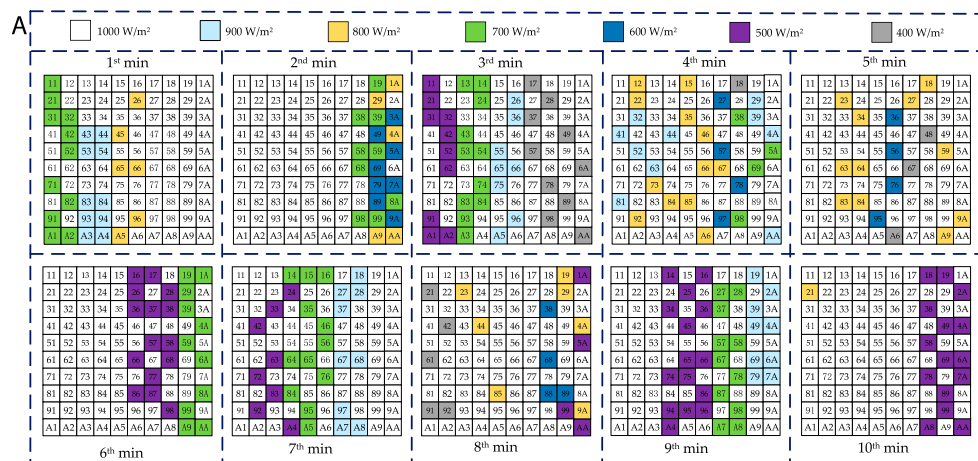
Power curves of BESS, joint PV-BESS station and PV plant without optimization.



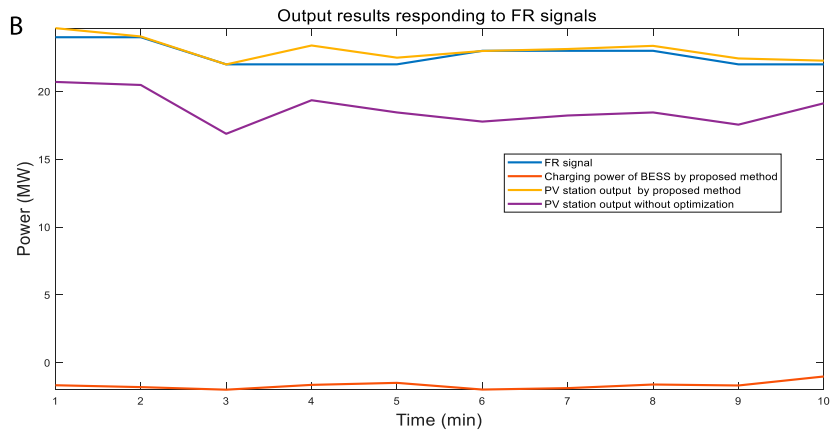
Comparison of power deviation and profit.

FIGURE 4

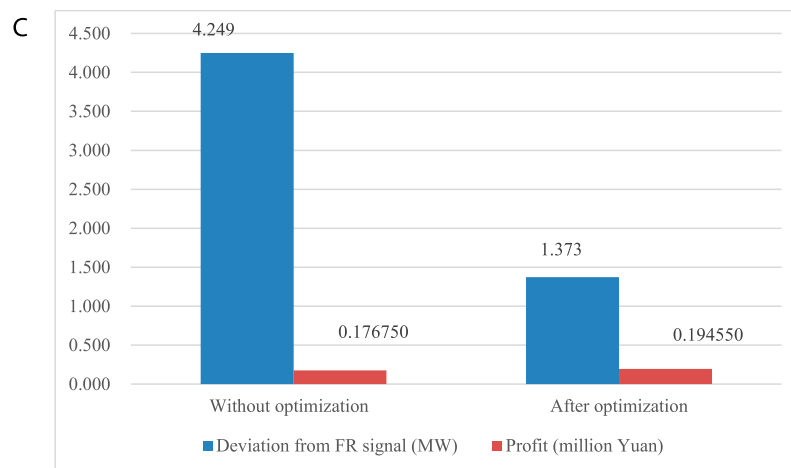
(A) Shading distribution of PV array after reconfiguration. (B) Power curves of BESS, joint PV-BESS station and PV plant without optimization. (C) Comparison of power deviation and profit.



Shading distribution of PV array after reconfiguration.



Power curves of BESS, joint PV-BESS station and PV plant without optimization.



Comparison of power deviation and profit.

FIGURE 5

(A) Shading distribution of PV array after reconfiguration. (B) Power curves of BESS, joint PV-BESS station and PV plant without optimization. (C) Comparison of power deviation and profit.

a FR command of decreasing power output from dispatch department. Therefore, the FR signal under high grid frequency is designed as below:

$$P_{FR}(t) = \begin{cases} 16, & 1\text{min} \leq t < 2\text{min} \\ 15, & 3\text{min} \leq t < 8\text{min} \\ 16, & 9\text{min} \leq t < 10\text{min} \end{cases} \quad (25)$$

After the optimization of PV reconfiguration by MOGEO, the shadow is dispersed to the whole array as demonstrated in Figure 4A. Moreover, the power curves of BESS, joint PV-BESS station and PV plant without optimization are depicted in Figure 4B. Obviously, the proposed reconfiguration method based on MOGEO effectively mitigate the impact of PSC and consequently enhance the upper limit of PV output. With the cooperation of BESS, the proposed technique achieves the aim of reducing the deviation between output power of joint PV-BESS and FR signal than that without reconfiguration optimization. In addition, the power biases from FR signal and profits before and after optimization are shown in Figure 4C.

Response to low frequency of grid

Apart from high frequency response, the simulation test for low frequency response is also performed, and the FR signal is designed as follows:

$$P_{FR}(t) = \begin{cases} 24, & 1\text{min} \leq t < 2\text{min} \\ 22, & 3\text{min} \leq t < 5\text{min} \\ 23, & 6\text{min} \leq t < 8\text{min} \\ 22, & 9\text{min} \leq t < 10\text{min} \end{cases} \quad (26)$$

The shadow distribution after PV reconfiguration is demonstrated in Figure 5A. Moreover, the power curves of BESS, joint PV-BESS station and PV plant without optimization are depicted in Figure 5B. And the power output of PV station is more closed to FR signal than that of high frequency response. Besides, the proposed reconfiguration model effectively enhances the upper limit of PV output and consequently enhance the margin space of power modulation. What's more, the power biases from FR signal and profits before and after optimization are shown in Figure 5C.

Conclusions and perspectives

In this work, a novel PV station participating FR technique based on PV array reconfiguration and BESS is put forward. And the simulation results verify that the proposed method contributes to the frequency response of PV station. Two cases are designed and tested. The main conclusions of this work are summarized as below:

- 1) MOGEO can effectively find satisfactory solution which can meet both of profit maximization and power deviation minimization;
- 2) The improved ideal point decision making method is proposed to get optimal weight coefficients of each objective more fairly;
- 3) By proposed technique, the profit of PV station is increased by 8.4 and 10.07% respectively in the high and low frequency response simulation tests; meanwhile the power deviation from FR signal is decreased by 19.98 and 67.69% in the high and low frequency response tests.

The future works will focus on the following issues:

- Hardware-in-the-loop experiments should be executed to testify the practical influence and algorithm convergence rate of proposed technique;
- Hardware implementation method of PV array reconfiguration deserves more attention.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

JZ: Conceptualization, Writing-Original Draft, Formal analysis; CL: Formal analysis, Software, Supervision; KL: Project administration, Resources.

Conflict of interest

Author JZ was employed by the company State Grid Corporation of China.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 02 August 2022

ACCEPTED 15 August 2022

PUBLISHED 02 September 2022

CITATION

Peng Z, Gao X, Chen R, Yang H and
Zeng Z (2022), A dynamic hierarchical
partition method for active distribution
networks with shared energy
storage aggregation.
Front. Energy Res. 10:1009972.
doi: 10.3389/fenrg.2022.1009972

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A dynamic hierarchical partition method for active distribution networks with shared energy storage aggregation

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KEYWORDS

shared energy storage aggregation, cluster partition, active distribution networks, renewable energy, community detection

1 Introduction

The high penetration of renewable energy sources in distribution networks increases the difficulty of centralized operation and regulation (Chai et al., 2018; Magdy et al., 2021; Zhang et al., 2022). To improve the integration and schedulability of distributed energy, various distributed control methods based on the distributed generation cluster are proposed in (Muhtadi et al., 2021; Patel et al., 2022). The premise of realizing distributed control of distribution network is the reasonable division of distribution network cluster, which can be found in many studies. The electric distance is one of the most commonly used indicators of cluster division in distribution networks (Lagonotte et al., 1989). Ref (Islam et al., 2014), separated the network into multiple regions clusters in view of the electrical distance, and proposed a decentralized adaptive emergency control scheme to stabilize the voltage of power system. According to the improved modularity index, the distribution network with distributed photovoltaic systems was divided into multiple clusters (Zhao et al., 2017). Furthermore, k-means algorithm was applied in (Cotilla-Sanchez et al., 2013) to divide the power network. Vinothkumar et al., comprehensively considered the planning prospect of distribution network and used hierarchical clustering algorithm to obtain the best siting for distributed generation (Vinothkumar and Selvan, 2014). The indexes and algorithms of cluster division are studied in (Cotilla-Sanchez et al., 2013; Vinothkumar and Selvan, 2014; Liang et al., 2020), which take different demands of distribution network operation planning and scheduling into account. However, there are rare studies that consider the shared energy storage in cluster division.

In this paper, a dynamic partition method of the shared energy storage and prosumers based on community detection algorithm is proposed. The main opinions of this paper are as follows: 1) A comprehensive performance index of cluster division considering network structure and function is proposed. The local comprehensive index and global comprehensive performance index are established on the basic of the structural index and the functional index. The former is the combination of the electrical coupling index and spatial distance index, and the latter adopts the storage load demand matching index.

Based on the comprehensive performance index, the shared energy storage and prosumers in the whole region are divided into multiple internally closely connected and externally non-interfering storage prosumer clusters ultimately; 2) A hierarchical method based on the adaptive k-means clustering is put forward of shared energy storage. Through the adaptive k-means clustering algorithm, the energy storage resources, which belong to the same cluster, are finally segmented into multiple shared energy storage sets with different loss characteristics and transient response characteristics.

2 Cluster partitioning of active distribution networks with prosumers

2.1 Cluster division indicators of active distribution networks

Firstly, the shared energy storage and prosumers are preliminarily clustered from the aspects of electrical coupling degree, geographical spatial correlation and supply-demand balance. The specific cluster division indexes are as follows:

The electrical coupling degree index reflects the mutual influence of electrical quantities between nodes where prosumers and shared energy storage are located in. The comprehensive electrical distance between various nodes is adopted as the electrical coupling degree index in this paper. Due to the strong coupling relationship between active and reactive power in distribution network, it is essential to comprehensively consider the impact of active and reactive power on node voltage when partitioning. As well as the relationship between the two nodes is not only related to itself, but also related to other nodes. Therefore, the comprehensive electrical distance is the weighted sum of the comprehensive electrical active distance, which can be calculated by the Euclidean distance method based on node voltage active power sensitivity, and the comprehensive electrical reactive distance, which can be obtained with the analogous calculating method.

The spatial geographical location index is applied to describe the geospatial correlation degree between distributed park prosumers and shared energy storage resources. Geographically close distributed energy sources have high similarity in power waveform, which is convenient for unified prediction of user-side distributed energy. Meanwhile, the proximity of prosumers and shared energy storage in spatial location is suitable for unified collection of energy storage information, which is conducive to real-time transmission of user demand data and timely response of shared energy storage services. The Euclidean distance of geographical space is used as the spatial location index in this paper. Taking the weighted sum of the electrical distance and the spatial geographical distance as the comprehensive distance, which can be defined as the edge

weight of the network nodes of modularity index, so as to obtain the improved modularity index (Zhao et al., 2017), which can comprehensively describe the structural strength of the cluster from both the electrical topological structure and the spatial geographical structure.

Except for taking the close connection degree of the topological structure between prosumers in the park into consideration, the storage and prosumers partition should also ensure that the shared energy storage resources within the cluster can satisfy the active and reactive power demand as much as possible. According to the minimum active power limit negotiated by the shared energy storage aggregator and the prosumers in advance, the active power charge and discharge unbalance of energy storage in any cluster z can be obtained. Assuming that the intra-day time length is T , the active demand matching index of cluster z can be acquired based on the charge and discharge imbalance of energy storage. Besides, the reactive power of each node in the cluster should be balanced locally as far as possible to reduce the reactive power transmission across clusters. Based on the maximum historical voltage deviation of each node and the reactive power sensitivity matrix, the minimum reactive power demand (Zhao et al., 2017) required in the cluster can be figured out and then the reactive demand matching index of cluster z is obtained, which reflects the reactive power balance ability of the cluster. When the inverter capacity of energy storage in the cluster is greater than the sum of reactive power requirements, the demand reactive power of this cluster is completely satisfied. Consequently, the local comprehensive index of cluster is the weighted sum of the modularity index, the active demand matching index and the reactive demand matching index, and the global comprehensive index is the average of the local comprehensive index.

2.2 Cluster partitioning algorithm based on community detection

The community detection algorithm is used in the optimal cluster division to achieve the maximum global comprehensive index (Javed et al., 2018). The local comprehensive index of each cluster is used as the local optimization objective, and the global comprehensive index of all clusters is regarded as the global optimization objective for adjusting the cluster division. Then, the community detection algorithm is applied to divide the shared energy storage and prosumers into clusters. The specific process is as follows:

- 1) Initialize each node as a separate cluster;
- 2) For any node m , moving it to the cluster where node n is located, and the increment of local optimization objective after joining is calculated and recorded. The node with the maximum increment of local optimization target after joining is divided into the cluster where node n is located;
- 3) Repeat step 2) until the

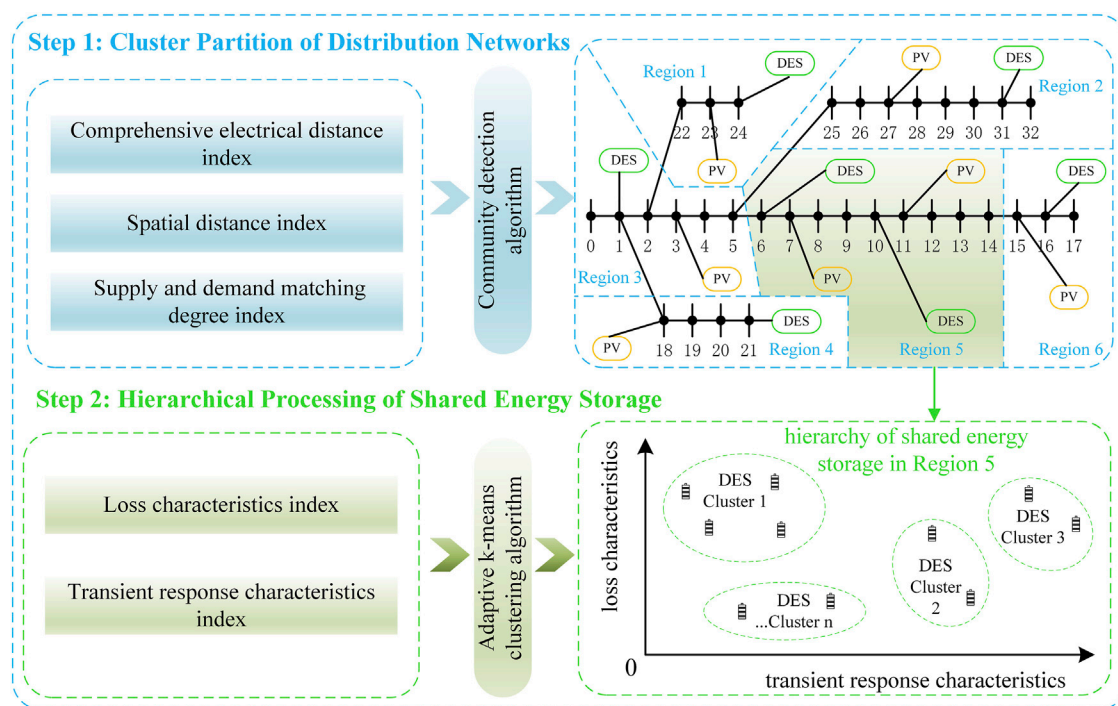


FIGURE 1
Dynamic hierarchical partition schematic diagram.

global optimization objective reaches the maximum, and then the optimal clusters can be solved.

3 Hierarchical processing of shared energy storage aggregation

3.1 Multi-characteristic indexes of shared energy storage

In order to select the appropriate shared energy storage unit to achieve diversified application of energy storage in multiple scenarios with the minimum operating cost (Dai et al., 2021; Liu et al., 2021; Li et al., 2022), such as peak regulation and frequency modulation, renewable energy consumption, demand side response, reactive power compensation, and emergency reserve, the loss characteristics and transient response characteristics of energy storage can be hailed as the selection indicators and the energy storage resources with the same characteristics are aggregated and regulated optimally in this paper.

The shared energy storage resources are mainly composed of the energy-type energy storage, such as lithium iron phosphate battery, all-vanadium flow battery,

sodium sulfur battery and lead-acid battery, and the power-type energy storage including electrochemical supercapacitor and superconducting magnetic energy storage. The capacity and power loss characteristics of energy storage are determined by a series of energy storage loss characteristic parameters. The life loss of energy-type energy storage is related to the depth of discharge, the state of charge, and the charging/discharging power (Wang et al., 2020; Liang et al., 2022). The life of power-type energy storage is greatly limited by the number of charge and discharge cycles. These influencing factors can be expressed by the related loss characteristic parameters which are taken as the loss characteristic indexes of energy storage in this paper.

Different energy storage differs in active regulation capacity and regulation efficiency, which will affect the economy of shared energy storage and the stability of power system. Therefore, in the aggregation process of abundant shared energy storage, the regulation response time should be taken as one of its characteristic quantities. There is a specified relationship between the transient response time and the response time constant of energy storage, that is, the response time constant reflects the transient response speed. Thus, the response time constant is chosen to be the transient characteristic index of energy storage in this paper.

3.2 Dynamic partition method based on adaptive clustering

As one of the most commonly used clustering algorithms, k-means algorithm is uncomplicated and has fast convergence rate (Cotilla-Sanchez et al., 2013). The main feature of k-means algorithm is to randomly determine k initial clustering centers, divide the network into k regions on the basis of distance comparison, and minimize the sum of squared errors (SSE) of all points and their related clustering centers in the iterative process. However, the random k may lead the results converge to local optimum. For achieving the better partitioning results, the elbow method is used in this paper to optimize the selection of clustering center k and realize adaptive clustering additionally.

The shared energy storage in the cluster is divided by the improved k-means clustering. With the evaluation index SSE consisted of the loss characteristics and transient response characteristics of energy storage, the optimal number of clusters depends on the reduced contribution rate of SSE so as to achieve the adaptive clustering. The shared energy storage sets with different loss characteristics and transient response characteristics can be obtained additionally.

The schematic diagram of the dynamic hierarchical partition method described in this paper is presented in Figure 1. Firstly, for maximizing the global comprehensive performance index composed of the electrical coupling index, spatial location index, and storage demand matching index, the distribution network with the distributed energy storage and renewable energy is segmented into several clusters. Then, the shared energy storage in the cluster is processed hierarchically. Taking region 5 as an example, according to the loss characteristics and transient response characteristics, the hierarchical processing of shared energy storage resources in region 5 is completed by adaptive k-means clustering.

4 Discussion and conclusions

A dynamic partition mechanism of shared energy storage and distributed prosumers based on community detection algorithm and adaptive clustering is proposed in this paper. First of all, a global comprehensive performance index considering the electrical coupling degree, spatial location, and the demand matching degree of storage is established. With the goal of maximizing the global comprehensive

performance index, the community detection algorithm is used to divide the shared energy storage and prosumers into clusters. Then, for each cluster, according to the loss characteristics and transient response characteristics of energy storage, the reduction contribution rate of the k-means clustering evaluation index is introduced to realize the adaptive judgment of the optimal cluster number, so as to complete the hierarchical processing of shared energy storage resources in the cluster. The proposed scheme is a feasible and realistic cluster partition method, which can aggregate the shared energy storage with the same characteristics, simplify the difficulty of operation scheduling, and realize a variety of applications of energy storage with a low operating cost.

Author contributions

Writing the original draft and editing, ZP; Conceptualization, XG; Formal analysis, RC; Visualization and contributed to the discussion of the topic, HY and ZZ.

Funding

This work is supported by the Scientific Research Startup Fund for Shenzhen High-Caliber Personnel of SZPT (No. 6022310042k).

Conflict of interest

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 11 July 2022

ACCEPTED 15 August 2022

PUBLISHED 08 September 2022

CITATION

Yang G, Zhu Y, Zen F, Zhou S and Chen Y
(2022), Electromagnetic transient
characteristics and overvoltage
suppression strategy of renewable
energy-oriented power system
connected by gas-insulated
transmission lines.
Front. Energy Res. 10:991355.
doi: 10.3389/fenrg.2022.991355

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Electromagnetic transient characteristics and overvoltage suppression strategy of renewable energy-oriented power system connected by gas-insulated transmission lines

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New energy systems, such as wind power and photovoltaic and distributed power supply, in the power generation and grid-connected transmission system basically will use stronger insulation design, higher operational safety, and smaller footprint GIL equipment, while the new energy transmission system of the smart grid development trend requires accompanying the electronic transformer equipment to promote a large area. However, the current GIL equipment used in new energy transmission systems has caused great electromagnetic interference to the electronic equipment due to the compact layout of the equipment and the transient signals generated by normal operation, which has seriously restricted the development of smart grids and became a major obstacle to the grid connection of new energy systems. In order to study the characteristics and developmental law of transient electromagnetic interference signal of GIL equipment in new energy transmission and transformation system, this study proposes a dynamic arc model based on an optimized arc extinguishing criterion, verifies the correctness of the improved dynamic arc model through theoretical analysis, simulates calculation combined with the test measurement data, and compares and analyzes the simulation results with test measurement data to study the transient electromagnetic interference source signal during arc burning duration. The simulation results and test data are compared and analyzed to study the pulse steepness, size of the wave head, and overall waveform development law of the transient electromagnetic interference source signal during the arc burning process. It is concluded that the dynamic arc model based on the optimized arc extinguishing criterion can be better used to study the transient electromagnetic interference signal in the GIL equipment. Meanwhile, the transient electromagnetic interference signal has the characteristics of large amplitude and high frequency, the maximum overvoltage can reach 1.9 p.u., the UHF can reach 30 MHz, and the wave head rise time is about 12 ns. This study provides theoretical support for subsequent research on suppressing

transient electromagnetic interference source signals, improving the anti-electromagnetic interference performance of electronic devices, and is dedicated to solving the obstruction problem in the process of grid connection of new energy transmission and substation systems.

KEYWORDS

new energy transmission and substation, GIL, VFT signal, transient electromagnetic interference, simulation and test

1 Introduction

The goal of “carbon peaking and carbon neutrality” has begun to rapidly integrate with various medium- and long-term plans of various countries. For the corresponding power system, the focus of development is not only from the integrated development of “source network, load, and storage” but also to focus on the construction of new energy power generation systems. Traditional coal-fired power generation is gradually transitioning to new energy power generation methods such as wind, light, and nuclear energy. Under the background of policy increases, the systematic construction of new power transmission and transformation that matches the connection of power generation to the grid has been continuously upgraded. Among them, the new power transmission and transformation system of new energy power generation and grid connection basically adopts the design form of the user’s GIL equipment. On the one hand, the reason is that land resources have become tight due to urban development, and on the other hand, the indoor GIL equipment is safer and more reliable, and it is not easy to cause the rejection of the surrounding residents. Therefore, more and more new power transmission and transformation systems connected to the grid for new energy power generation use the GIL equipment.

At the same time, with the development of smart grids, the development trend of new energy transmission and transformation systems is the widespread use of electronic transformer equipment used in conjunction with the compact GIL equipment. As shown in Figure 1, compared

with the traditional open power transmission and transformation system, one of the major drawbacks of the GIL equipment is that the space is compact, so it is easy to ignore the electromagnetic interference under the premise of ensuring the insulation margin. At the same time, the transient signal generated by the equipment operation of the new energy grid-connected terminal GIS substation will have a serious folding reflection in the pipeline equipment (including the GIL equipment), thus further enhancing its hazard. According to relevant statistics, the failure rate of electronic transformer equipment that has passed the factory electromagnetic interference test has reached 30%, and the corresponding research shows that the main reason why electronic transformer equipment has not been widely promoted in new energy transmission and transformation systems is the high failure rate caused by the strong electromagnetic interference (Liu et al., 2012).

The electromagnetic environment within the substation is complex, and one of the most serious sources of interference is currently recognized as a fast transient signal (Zeng et al., 1996), that is, VFT (Very Fast Transient), which is generated by the GIL internal isolation switch. On the one hand, the isolation switch gear cannot perform automatic arc extinguishing, and on the other hand, the gate knife contact of the isolation switch moves slowly, which easily leads to arc pulling. Therefore, due to the VFT interference source signal that produces a large amplitude and high frequency during the operation of the GIL disconnect switch, the interference characteristics of

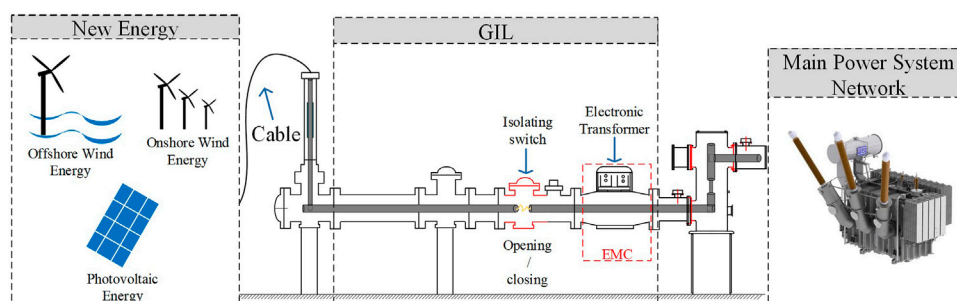


FIGURE 1
Schematic diagram of the grid connection process of the new energy system.

the VFT interference signal are the wave head rising in the ns level and the high-frequency component up to about 30 MHz (Zhao et al., 2015).

The key point of the VFT electromagnetic interference problem lies in the repeated reignition of the arc between the disconnecting switch action process breaks and the resulting repeated oscillation of the attenuated wave signal in the GIS pipeline constantly folded and reflected superimposed on the generated electromagnetic interference source signal (Chen et al., 2019). For the VFT problem at home and abroad, which began to be researched very early, the overall research trend can be divided into two major aspects, one is to ignore the complex arc process mode, with only a simple switch split instead, and rough simulation of the VFT characteristics can meet the engineering needs of a particular situation; and another research direction is to continuously optimize the arc model through theoretical calculations and simulation modeling to maximize the simulation of the arc development. However, the development process of the arc involves a variety of physical and chemical phenomena coupled, it is difficult to make a breakthrough in purely theoretical calculations, and thus the optimization of the simulation model is the mainstream trend of VFT research. For the arc simulation model research, the most commonly used method is to use the arc resistance characteristics of the arc to simulate the arc process and the literature (Meng et al., 2010) according to the measured data fit to get the arc resistance function model to simulate the study of the arc process generated under the action of the disconnecting switch, but the study is limited to a single-arc study and failed to achieve the modeling of the complete repeated arcing process. Lin et al., 2012aLin, Wang and Xu, 2012a) obtained the analytic equation of the VFT electromagnetic interference source signal from the theoretical point of view and then analyzed the development law of the signal, but the theoretical analysis was always unable to define the arc model as a function and therefore could not meet the current demand.

Because the traditional arc model of the arc extinguishing conditions is only the arc current natural over zero moment, and the actual arc energy conservation law does not match the situation. This study proposes an improved arc model to optimize the arc extinguishing criterion, through theoretical analysis, simulation modeling combined with actual test data to verify the feasibility of the improved arc model, and the use of simulation modeling to study the interference characteristics of the VFT electromagnetic interference source signal. The simulation data will also be compared with the test waveform to study the waveform signal steepness, wave head size, and the change of 10 consecutive single-arc ignition processes for the subsequent study to suppress the fast transient signal to

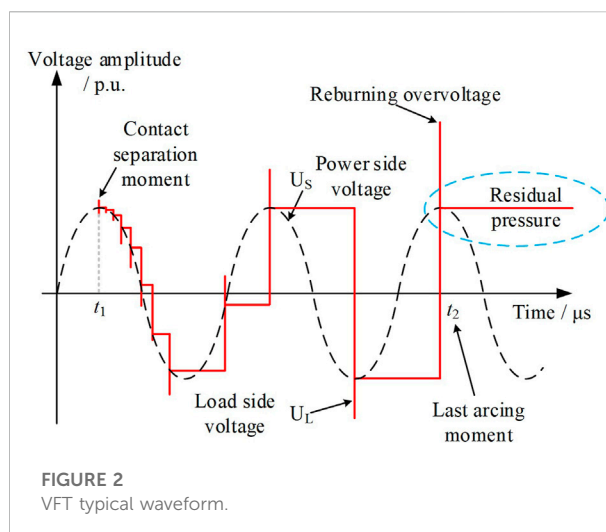


FIGURE 2
VFT typical waveform.

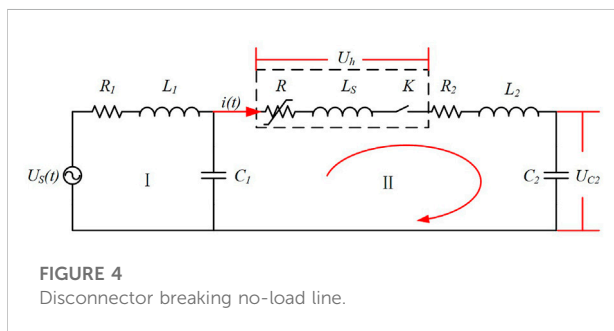
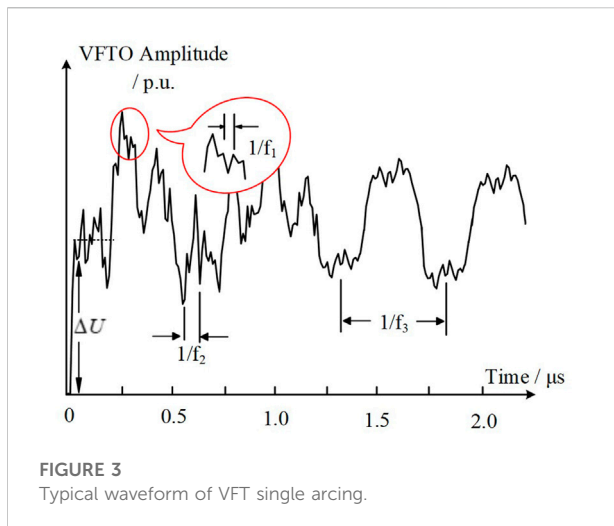
improve the electronic transformer. At the same time, the simulation data are compared with the measured waveform to study the pulse steepness, wave head size, and the waveform change of 10 consecutive single-arc combustion processes, which provides theoretical support for the subsequent research on suppressing the fast transient signal to improve the anti-electromagnetic interference performance of electronic transformers.

2 Theoretical analysis

2.1 Very fast transient typical waveform

The root cause of VFT interference source in the GIS device system is that the isolation switch has no arcing capability. The strong electromagnetic interference to the adjacent equipment is caused by repeated arc burning between the isolating switch knife edges due to dielectric breakdown and propagation of wave signals in the circuit. Figure 1 shows the typical VFT signal waveform of a no-load line cut by a disconnecting switch (Duan et al., 2015).

From Figure 2, we can see that from the moment the disconnect switch contacts are separated, the VFT signal begins to form, and the overall development trend of the waveform is presented as a continuous “ladder,” and the rise and fall of the “ladder” is consistent with the change in trend of the power supply side voltage U_s . At the same time, it is obvious that the maximum and minimum values of VFT appear at the “peak” and “trough” of U_s , respectively, which is because the “peak” and “trough” of U_s are both at the “peak” and “trough” of U_s . This is because the U_s “peak” and “trough” are the absolute maximum amplitude moment when the arc is more likely to occur. In addition, the



horizontal line of each “ladder” represents a complete single-arc burning process, and the blue-dotted waveform in Figure 2 is a complete single-arc waveform.

According to relevant standards, the single arcing part of the VFT signal is basically composed of four parts (Wang et al., 2000), and the typical waveform is shown in Figure 3.

Figure 3 shows that VFT, as single pulse waveform of arc, is delta ΔU superimposed vibration attenuation with the change in trend of high-frequency distortion, and the high-frequency waveform has three main parts: the UHF f_1 component part determines the high-frequency distortion, the ultra-high frequency f_2 component part determines the signal peaks, and the high-frequency f_3 component determines the overall trend of oscillation waveform. The f_1 and f_2 components are partly caused by the obvious mutation of reflection and wave impedance in the signal propagation process, while the main frequency part of the VFT signal is f_3 component, which is generated by resonance caused by the equivalent capacitance characteristic of the external equipment, and this part can be analyzed through theoretical calculation.

2.2 Theoretical calculation of very fast transient dominant frequency component

Taking the disconnector breaking the no-load line as an example, the schematic diagram is shown in Figure 4, and the combination of R , L_s , and K in the dotted box in the figure is equivalent.

Assuming that at some point t is in the burning arc state, the switch K is closed and the loop II is turned on, and according to Kirchhoff's law, the following equation is satisfied:

$$L_2 \frac{di(t)}{dt} + \frac{1}{C_1} \int_0^t i(t) dt + R_2 i(t) + u_{C_2} + u_h = U_1(0) \quad (1)$$

C_1 and C_2 are the residual voltage before $U_1(0)$ and $U_2(0)$, respectively, at time t , U_h is the voltage at both ends of the isolating switch, namely, the arc voltage. $i(t)$ is the current flowing through the isolation switch, that is, the arc current. Meanwhile, according to the energy conservation principle of inductor L_s and capacitor C_2 , it can be known that

$$\begin{cases} u_{C_2} = \frac{1}{C_2} \int_0^t i(t) dt + U_2(0) \\ u_h = i(t)R + L_s \frac{di(t)}{dt} \end{cases} \quad (2)$$

According to the knowledge of differential equations, the condition that the equation has a solution is to satisfy Eq. 3;

$$(R_2 + R) < 2 \sqrt{\frac{(L_2 + L_s)(C_1 + C_2)}{C_1 C_2}} \quad (3)$$

At this time, resonant overvoltage will be generated in the circuit, which is the f_3 component of the VFT signal. Let the capacitance C be the series value of C_1 and C_2 and solve the differential equation to obtain

$$p_{1,2} = -\alpha_0 \pm j\omega_0 \quad (4)$$

According to the formula characteristics of differential function solution, in the abovementioned formula, ω_0 determines the oscillation of the function, which is called the natural angular frequency. α_0 determines the attenuation speed of the function, which is called the attenuation coefficient. Further solution can be obtained as follows:

$$\begin{cases} \alpha_0 = \frac{[R_2 + R]}{[2(L_2 + L_s)]} \\ \omega_0 = \sqrt{\frac{1}{(L_2 + L_s)C - \left[\frac{R_2 + R}{2(L_2 + L_s)}\right]^2}} \end{cases} \quad (5)$$

It can be seen from Eq. 5 that the inductance and resistance value on the load side are the determinants of signal attenuation

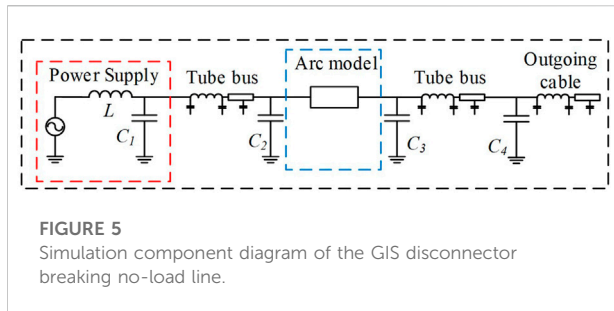


FIGURE 5
Simulation component diagram of the GIS disconnector breaking no-load line.

speed, while all component parameters in the loop, including the inductance, capacitance, and line resistance on the power side and the load side of the isolating switch, together determine the frequency of signal oscillation. Assuming that C_0 is a constant, the following equation can be obtained:

$$\begin{cases} i(t) = C_0 e^{-\alpha_0 t} \sin \omega_0 t \\ U_{C2}(t) = C_0 (1 - e^{-\alpha_0 t} \cos \omega_0 t) \end{cases} \quad (6)$$

It can be seen from Eq. 6 that the equipment connected by the isolation switch close to the line side, taking C_2 as an example, is subjected to oscillation attenuation of the VFT interference source signal, and the basic waveform of $U_{C2}(t)$ is the shock pulse superimposed on the attenuation oscillation waveform. The previously derived calculation results show that the main frequency f_3 component of the VFT signal is partly generated by resonance caused by line capacitive parameters, that is, the line capacitive parameters determine the main development trend of the VFT signal (Shen et al., 2020).

3 Modeling and simulation

3.1 Modeling background

Taking the GIS disconnector breaking the no-load line as the research background and selecting the commonly used transient analysis software EMTP of the power system as the research carrier, it is necessary to establish the EMTP equivalent circuit model of each equipment element. The most common method is to obtain the equivalent model and parameters of the element by means of field circuit combination (Duan, 2016; Kang, 2016). For example, the power system is equivalent to the ideal power supply and internal resistance, and the line is equivalent to the wave impedance element of impedance Z and wave velocity V . Considering the complexity of the overall GIS disconnector disconnection no-load line model, some components need to be combined and simplified. The simplified topology is shown in Figure 5.

The system equivalent model of capacitive component is more, and the equivalent capacitance is research emphasized,

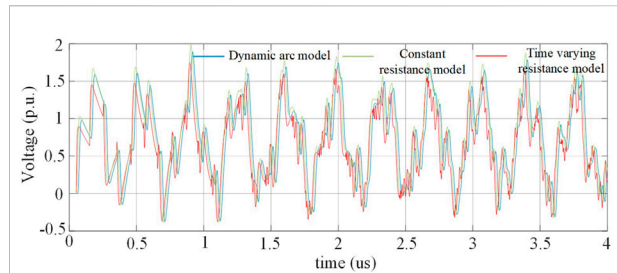


FIGURE 6
Simplified equivalent circuit diagram.

thus merging the processing capacity equivalent to the system parameters. Figure 4 shows that C_1 is the transformer equivalent entrance capacitance in parallel wire casing of capacitance, C_2 for transformer exports to lateral load isolation switch all the basin insulator GIS pipeline the sum of the equivalent earth capacitance in parallel, C_3 is the equivalent ground capacitance of the load-side isolator, and C_4 is the sum of the equivalent ground capacitance of all basin insulators in the GIS pipeline from the load-side isolator to the outlet bushing in parallel.

3.2 Single-arc burning model

A key point in the simulation modeling of the VFT electromagnetic interference source signal is the processing of the arc model. Currently, there are mainly three kinds of arc models for research for single-arc burning: fixed resistance, time-varying resistance, and dynamic resistance model. The fixed resistance model represents the whole process with the simplest stable arc burning state, and the current relevant research is based on the measured arc data using software fitting to obtain a specific value of 0.5Ω for the arc resistance during stable arc ignition (Tian et al., 2013). The time-varying resistance model is an arc path resistance change function roughly fitted according to relevant data (Liu et al., 2013), expressed in Eq. 7, but the limitation is that the parameters cannot be modified under different working conditions.

$$R(t) = 10^{12} e^{-t \cdot 10^9} + 0.5 e^{t \cdot 10^6} \quad (7)$$

The dynamic model is mainly based on Cassie and Mayr arc theory, both of which are assumptions based on the arc path arc energy variation law (Lin et al., 2012).

Taking Cassie's model as an example, its formula is summarized as follows:

$$\frac{1}{g} \frac{dg}{dt} = \frac{1}{\theta} \left[\frac{E^2}{E_0} - 1 \right] \quad (8)$$

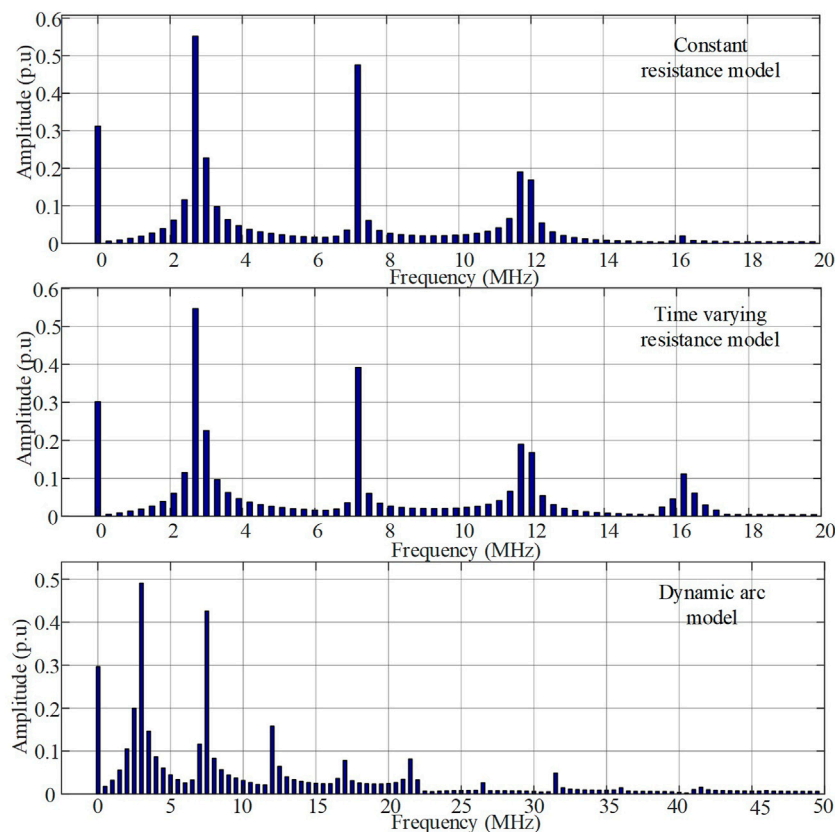


FIGURE 7
Frequency analysis of the fast transient voltage signal under the single arcing model.

where E is the arc potential per unit length in the arc burning state, θ is the arc burning time constant per unit length, g is the arc conductance, and E_0 is the voltage peak at both ends of the isolating switch blade. In the Cassie model, E_0 is constant by default, so it is suitable for the case of large arc current.

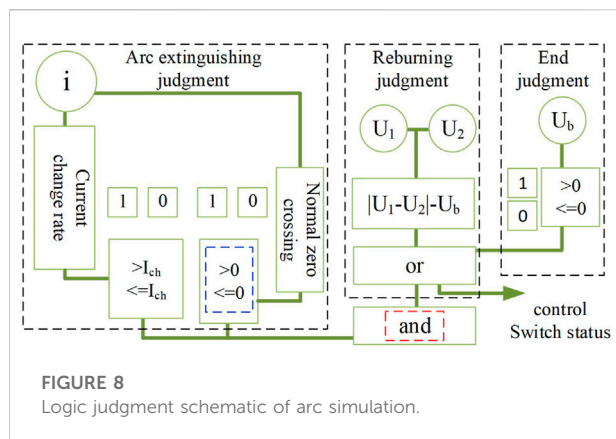
Three single-arc burning models were simulated and compared, and the fast transient voltage signal was obtained as shown in Figure 6.

As can be seen from Figure 6, the fixed-value arc resistance model, the time-varying arc resistance model, and the dynamic arc of a single-arc simulation results are basically the same, with only minor differences in the details of the magnitude. Also, it is obvious that the fixed-value resistance model only considers the stable arc state, so the basic peak voltage is larger than the results of the other two models, while the arc resistance of the arc extinguishing stage will instantaneously and rapidly increase. The simulated time-varying resistance model for this peak voltage is the smallest, and the dynamic arc model results between the two are more in line with the

actual results. Further Fourier analysis of the results is shown in Figure 7.

As the fast transient signal spectrum within 20 MHz frequency is determined by the parameters of the circuit components, the variable arc resistance will change the amplitude of different frequency parts, and dynamic arc model consideration is more realistic, making the frequency composition more complex. This point from the Fourier analysis results can be observed: three models to generate the waveform frequency composition are more complex, fixed-value resistance model and time-varying resistance model. The main frequencies of the models are smaller, both around 12 MHz, with 2.6, 3, 7, and 12 MHz as the main ones, which are small overall. In the dynamic resistance model, the frequency is more complicated due to the fluctuation of the arc resistance in different stages, except that the frequency composition is similar to that of the other two waveforms within 12 MHz, and the 17 and 21 MHz parts also account for a significant amplitude.

To sum up, the single-arc model is more inclined to the dynamic electric group model.



3.3 Improved dynamic arc model based on the optimized arc extinguishing criterion

The process of the electric arc is the repeated cycle of arc initiation, arc ignition, and arc extinguishing, i.e., the arc is continuously reignited, so the establishment of the reignited arc model is the purpose of the study, and the connection of multiple single-arc ignition models based on the dynamic resistance model into the complete arc ignition process by means of arc ignition and arc extinguishing judgment is the focus of the study. In the literature (Teng, 2013), a model based on the logical judgment language for reignition and arc-extinguishing stage judgment is proposed to realize preliminary arc full process simulation, but the limitation is that the logical judgment language of the arc-extinguishing module is too idealized, and the default arc current naturally passes zero when the arc is extinguished, and the actual study finds the dissipation of the arc energy as the direct cause of arc extinguishing. Therefore, the model in the arc extinguishing judgment is used to distinguish between frequency over zero and high-frequency oscillation over zero. Two different arc currents over the zero mode of logic are not reasonable, only the natural over zero judgment language is set, the arc current over zero is only a necessary condition for arc extinguishing, and the arc current over zero when the arc energy will not be just consumed, so the simple arc current over zero judgment is not only enough to conclude that the arc extinguished but also needs to assist at this time that the smaller the rate of change of the arc current. The lesser the arc energy change tends to be smooth, and the arc does not have arc extinguishing conditions (Meng et al., 2010).

According to the logic judgment ideas proposed in the literature (Teng, 2013) to optimize the arc extinguishing criterion to generate an improved dynamic arc model, the model of the arc ignition judgment logic is relatively simple, and the arc extinguishing state at a certain moment when the voltage difference between the two ends of the isolation switch

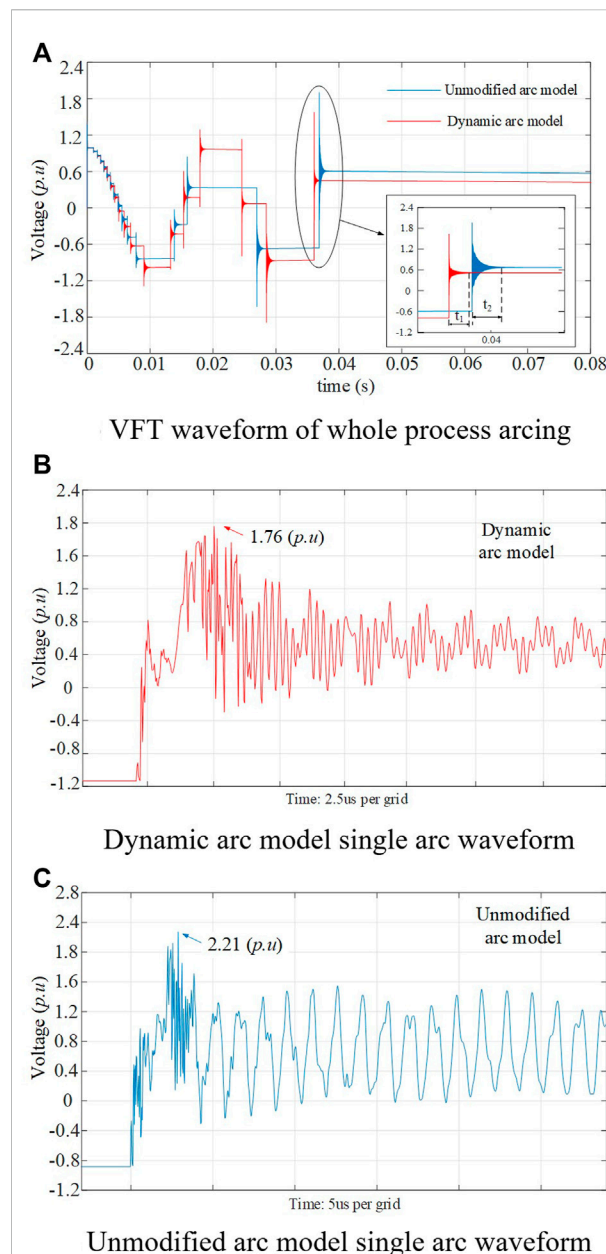


FIGURE 9
Comparison of VFT simulation results under different arc models. (A) VFT waveform of whole process arcing (B) Dynamic arc model single-arc waveform (C) Unmodified arc model single-arc waveform.

cutter is greater than the dielectric breakdown strength at that moment is the occurrence of arc ignition. The arc extinguishing criterion has been optimized for the arc current over zero when the arc is extinguished to assist the current change rate criterion at this time, and the two are with the gate. The relationship between the two is with the gate. The overall logic of the improved dynamic arc model is shown in Figure 8.

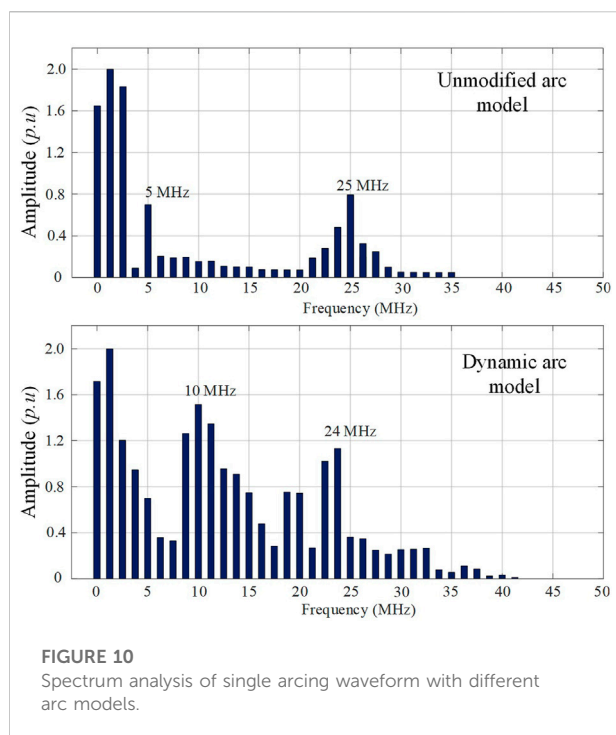


FIGURE 10
Spectrum analysis of single arcing waveform with different arc models.

As shown in Figure 8, the logic judgment module of the improved dynamic arc model is mainly divided into three parts, the arc extinguishing criterion, the arc burning criterion, and the end criterion, in which the end criterion is the logic language to determine whether the operation of the isolation switch is over. U_b is the dielectric breakdown voltage of the knife port, which varies with the size of the knife port spacing, that is, as a function of time t . The input quantity of the arc burning module is the voltage at both ends of the isolation switch knife port U_1 and U_2 and the input of the arc extinguishing criterion is the arc current $i(t)$ and through the software function automatically obtains the previous arc current $i(t-\Delta t)$ at the moment t . I_{ch} is a measure of the smaller rate of change of current, and the specific value is determined with the cutter spacing and SF6 concentration of the GIL disconnecting switch gear, and the value taken in the simulation is a reference value according to the literature (Zheng, Wu, 2010) “and” indicates with the gate logic that the logic model mainly controls the switch division and closure and is used to put in and out of the single arc burning model.

3.4 Simulation result

Based on the simulation topology in Figure 4 and the dynamic arc model after the optimization of the quenching criterion, the voltage level is 330 kV. The isolation switch is simulated to split and close the no-load line, focusing on the waveform of VFT on the equivalent ground capacitance C_2 of the

no-load line. The simulation results are shown in Figure 9. The simulation step length is 35 ns, and the simulation duration is 8 ms.

As shown in Figure 9A, the whole process of the arc waveform presents a “ladder” shape, with the theoretical analysis of typical VFT development patterns being consistent. At the same time, comparing the two arc models, the simulation results after optimization criterion arc energy attenuation law conforms to the objective laws, and the overall number of the arc model improved more. In addition, the signal attenuation of the improved single arc burning is faster ($t_2 \gg t_1$). It can be seen from Figure 9B and Figure 9C that the single-arc burning waveform of the improved arc model is a typical pulse signal superposition oscillation attenuation waveform. By comparison, the simulation results of the improved dynamic arc model after the optimization of the arc extinguishing criterion are more consistent with those of the typical waveform of the VFT single-arc burning.

Further analyses of the spectrum of the single-arc waveform of the two arc models are shown in Figure 10.

It can be seen from Figure 10 that the spectrum within 20 MHz in the single-arc signal waveform of the improved arc model is more complex and can better simulate the actual arc burning process, and the UHF part beyond 35 MHz can also be simulated by the improved arc model because the variable arc resistance will change the amplitude of different frequency parts, while the improved dynamic arc model is more practical and makes the frequency composition more complex.

In conclusion, the simulation model after optimizing the judgment logic can well-realize the whole simulation process of VFT, so it is feasible to simulate the development law of the VFT signal by this model.

4 Comparison between simulation and VFT characteristics

4.1 Build test platform

In order to minimize external interference, a GIS disconnector on–off no-load line test platform is chosen. The layout diagram of the platform is shown in Figure 11. The dotted box on the right represents the power side. The test process is as follows: first, the platform is charged without the load, and the circuit breaker is opened after a period of time. Then, the voltage and current signals are measured at the corresponding measurement position when the disconnector on the line side is opened, and the test platform is actually boosted by 330 kV.

During the preliminary test, the voltage is boosted to 330 kV. To facilitate the corresponding analysis with the simulation data, the action process lasts for 8 ms, and the test also considered the test item of the effect of the outgoing bushing with a capacitive load on the VFTO signal, and the purpose of the outgoing

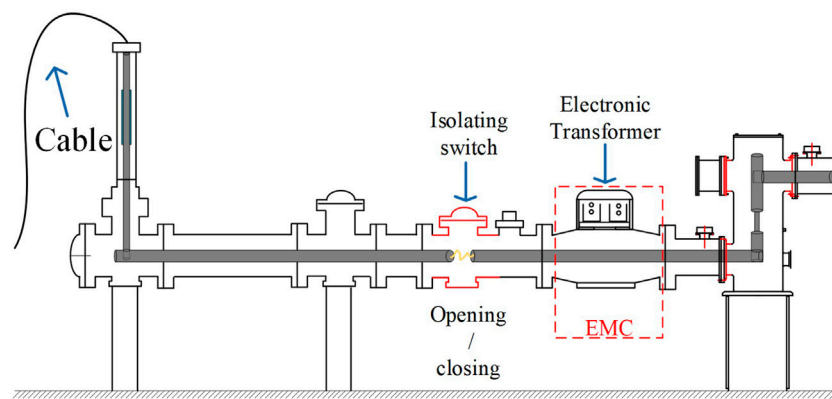


FIGURE 11

Layout of field test platform device.

TABLE 1 Test measurement plan.

Voltage/kV	Capacitive load/PF	Operation type
330	10,000	Opening
		Closing
	0	Opening
		Closing

bushing with a capacitive load is to simulate the capacitive effect of the no-load long line. Each item is opened and closed several times to eliminate the randomness. The measurement items are divided into the following four cases, as shown in Table 1.

Each group of tests are opened and closed several times. This is because the opening and closing process of the disconnector has strong randomness, so the strong VFT interference signal is taken for many times. The waveform amplitude and frequency of the measured data of the four groups of tests are close, but the measured results show that the VFT interference signal generated by the opening operation is stronger than that generated by the closing operation. The reason is that there will be residual voltage in the line before the opening operation, and the residual voltage is opposite to the voltage on the power side. The breakdown voltage at both ends of the knife edge of the disconnector greater and produces a stronger pulse part. In addition, the interference signal with no-load is stronger than that with a capacitive load because the main frequency of the VFT signal is resonance caused by capacitive elements. Under the conditions of this test, the equivalent capacitance value of the no-load line meets the resonance conditions, but increasing the capacitive load will destroy the resonance conditions and reduce the overvoltage amplitude. The strongest transient signal is imported into MATLAB as shown in Figure 12.

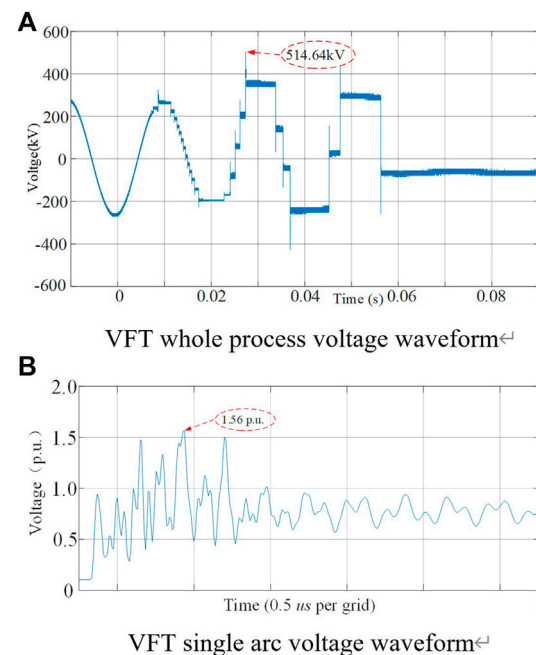
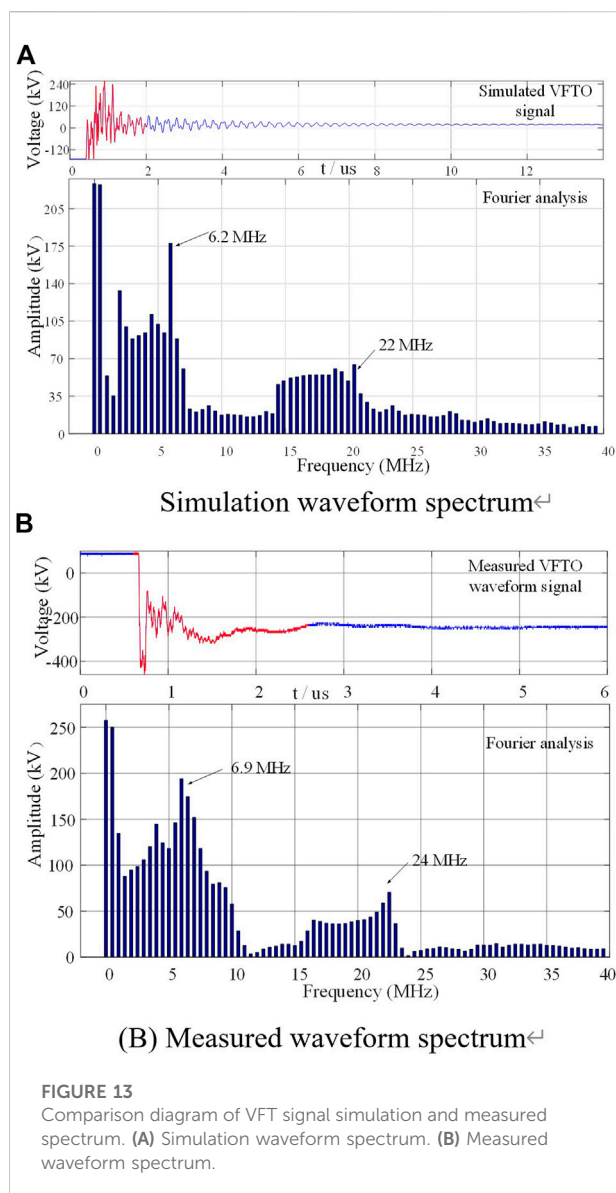


FIGURE 12

Measured VFT waveform generated by disconnector opening and closing no-load line. (A) VFT whole process voltage waveform. (B) VFT single-arc voltage waveform.

It can be clearly seen from Figure 12A that the measured VFT electromagnetic interference signal is consistent with the theoretical analysis and simulation results and presents a “ladder” shape as a whole. Due to the electromagnetic interference of the measured environment, the waveform of the measured data is wide during arcing, which is different



from the simulation. The strongest single arcing waveform in the measured data can be seen from Figure 12B, which is also consistent with the previous analysis. It is the pulse wave superimposed oscillation attenuation signal. The VFT maximum overvoltage of the overall measured data is 514.64 kV (1.91 p.u), which is greater than the maximum overvoltage amplitude of 1.76 p.u simulated under the same conditions, and the measured data are random, so the maximum overvoltage may not be the strongest signal. The VFT electromagnetic interference signal generated in the opening and closing process of the disconnecter is strong, which will seriously threaten the insulation and electromagnetic compatibility performance of the adjacent equipment.

Furthermore, the characteristics of the VFT electromagnetic interference source signal are analyzed, the single-arc burning

waveform of simulation and test results is selected, and the spectrum of waveform and the characteristic quantity of wave head steepness are extracted for comparative analysis and research.

4.2 Spectrum comparison between simulated and measured data

According to the theoretical analysis, the fundamental frequency of the VFT signal determines the development trend of the arc burning waveform in the whole period, while for the single-arc burning waveform, the focus belongs to the composition of high frequency and UHF. The strongest single arcing waveform of simulation data and measured data is analyzed by MATLAB. The results are shown in Figure 13.

The waveform diagram in Figure 13 is the signal source of analysis, the red part is the waveform period selected by Fourier analysis, the analysis selection period is about 2 μ s, the histogram is the Fourier analysis spectrum, and the basic frequency during analysis is 0.5 MHz. The waveforms of the simulated and measured last ignition arc selected for this study were subjected to Fourier analysis. Due to the random nature of the process, the last ignition arc of the simulated results occurred at the forward wave peak, while the last ignition arc of the measured results occurred at the reverse wave peak. However, the analysis of the spectrum of the single-arc-burning waveform and the positive and negative directions of the voltage and current signals are not directly related and do not affect the conclusion of the analysis.

It can be seen from Figure 11 that the frequency spectrum of the single arcing waveform in the VFT electromagnetic interference source signal obtained by the two methods is similar. The high frequency of the simulation signal is concentrated at about 6.2 Mhz, and the corresponding amplitude reaches about 175 kV, while UHF is concentrated at about 22 MHz, and the corresponding amplitude is only about 70 kV. The high frequency of the actual VFT waveform is slightly higher, 6.9 Mhz, UHF is concentrated at 24 MHz, and the corresponding amplitude of the two frequencies is slightly higher than the simulation value. This is because the simplified processing of equivalent ground capacitance of some equipment during simulation and because the measured acquisition is subjected to environmental electromagnetic interference, and the amplitude proportion of lower frequency in the spectrum is significantly greater than that of simulation. On the whole, they have high spectral consistency.

The spectrum of the VFT electromagnetic interference source signal is complex, the maximum frequency can exceed 40 MHz, and the amplitude of some high-frequency signals is strong, which will cause strong electromagnetic interference to the primary equipment.

TABLE 2 Statistics of wave head steepness of the last 10 single arcing waveforms of VFT during opening.

	Test D (p.u/ns)	Simulation D (p.u/ns)
First	0.1038	0.0996
Second	0.0897	0.0792
Third	0.0835	0.0846
Fourth	0.0882	0.0955
Fifth	0.0728	0.0769
Sixth	0.0943	0.0898
Seventh	0.0773	0.0659
Eighth	0.0653	0.0452
Ninth	0.0864	0.0708
Tenth	0.0963	0.0746

4.3 Comparison of wave head steepness between the simulated and measured waveform data

The wave head of the VFT signal refers to the pulse of waveform. It can be seen from Figure 2 that the wave head of the single-arc burning waveform is the first voltage “rise” after arc burning, which is expressed by Δu , and the voltage rise time of the wave head is very short, which is an ns-level surge. Li et al. (2015) point out that the more dangerous in VFT is the ns-level surge steep wave. The research shows that the surge phenomenon of the wave head of the VFT signal is due to the sudden change of voltage of static contact of the disconnecter and the dielectric breakdown of knife edge gap. The voltage on the static contact needs to suddenly change into the voltage on the power side of the moving contact, so it will form a surge of the NS wave head.

To analyze the dangerous degree of surge of the pulse wave head, we should not only pay attention to the amplitude of pulse wave but also the time consumed by the pulse wave rising to the peak, which is a very important factor. Chen et al. (2013) point out that the rising pulse wave time of the VFT signal is determined by the size of discharge gap. There are tips at both ends of the GIS disconnecter contact, which is prone to tip discharge. Therefore, the knife edge gap of the disconnecter is an uneven electric field, and the voltage required for breakdown discharge is small, resulting in a long time for wave head lifting, about 3–20 ns. Through the statistical analysis of many measured test data by Zhu et al. (2016), it is found that the average rise time of the single-breakdown arc waveform pulse where the VFT peak is located is within 12 ns.

The steepness D of the wave head is defined as the ratio of the lifting amplitude ΔU_1 of the wave head to the lifting time t_R of the wave head, including

$$D = \frac{\Delta U_1}{t_R} \quad (9)$$

As can be seen from Figure 11B, the measured data show that the wave head of single-arc burning is obvious, the rise time is about 13.93 ns, the amplitude $\Delta U_1 = 1.33$ p.u, and the wave head steepness $D = 0.0955$. As can be seen from Figure 8, the rise time of the wave head of single-arc burning is about 12.68 ns, the amplitude $\Delta U_1 = 0.98$ p.u, and the steepness of the wave head $D = 0.0773$. It can be seen that the lifting amplitude of the measured data is large, the wave head duration is long, and the wave head steepness of the maximum single-arc burning is greater than the simulation data.

For further comparison, the last 10 single arcing waveform data of the measured VFT waveform in the opening process are selected and compared with the simulation data under the same conditions. The statistical results are shown in Table 2:

It can be seen from Table 2 that the wave head steepness of the overall simulation result is slightly less than the measured data because the premise of simulation is the selection of equivalent parameters, which is different from the actual situation. At the same time, it can be seen that the overall development of the wave head steepness in the last 10 arcing of the measured data has no law to follow and has great randomness, which is also the main reason why the VFT electromagnetic interference signal has not been accurately analyzed at present. However, the wave head steepness in the simulation results of the optimized arc model is also consistent with the measured results. It is verified again that the model has desirable value in the research of the VFT electromagnetic interference signal.

At the same time, from the last 10 single arcing waveforms in the process of opening arcing, the more the VFT signal waveform in the process of opening, the steeper the wave head of the transient signal, and the stronger the harm due to the superposition of residual voltage.

5 Conclusion

New energy systems in power generation and grid-connected transmission and substation systems are basically used in the indoor GIS equipment, despite the stronger insulation design and higher safety and reliability of the GIS equipment, but the current new energy transmission and substation systems used in the GIS equipment due to the compact layout of the equipment lead to the VFT transient signal to electronic equipment, causing great electromagnetic interference, which seriously restricts the development of smart grid footsteps. It is also a major obstacle to the grid connection of new energy systems. In order to study the characteristics and development law of the VFT transient electromagnetic interference signal of the GIS equipment in new energy transmission and transformation system, the study uses theoretical analysis, simulation modeling combined with the experimental measurement method to reproduce the characteristics and development trend of the VFT electromagnetic interference signal by a dynamic arc model with

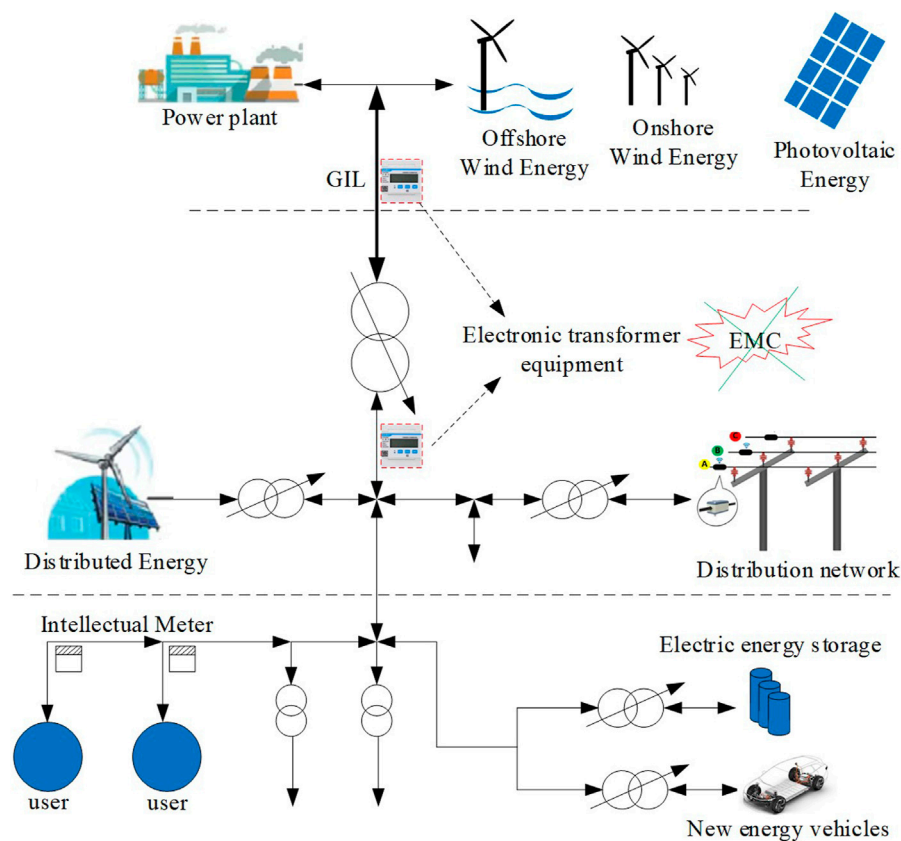


FIGURE 14
New power system structure diagram.

optimized arc extinguishing criterion and analyzes the spectrum and wave head characteristics of the VFT electromagnetic interference signal. The following conclusions are obtained.

- 1) The problem of VFT transient electromagnetic interference in the indoor GIS equipment used in new energy transmission and transformation systems is the main reason that restricts the development process of smart grid electronic transformer equipment to promote a large area.
- 2) The single-arc waveform of the VFT electromagnetic interference signal is a pulse voltage superimposed oscillation attenuation wave, and the repeated re-ignition of the arc makes the development of the arc waveform in the whole process showing a “ladder” change trend.
- 3) The improved dynamic arc model based on increasing the change rate of arc current and optimizing the arc extinguishing criterion can be used to study the VFT electromagnetic interference signal generated during the action of the GIS disconnector. The overall development trend of the simulation waveform and single-arc burning waveform are consistent with the theoretical analysis and measured results.
- 4) The maximum overvoltage of the VFT electromagnetic interference signal generated under the opening and closing action of the GIS disconnector can reach 1.9 p.u, UHF can reach 30 MHz, and the rise time of the wave head is about 12 ns. The VFT signal with large frequency amplitude, high frequency, and steep wave head will cause great insulation threat and electromagnetic interference to the equipment near the knife edge of the disconnector.
- 5) With the development of the power grid, the suppression of the VFT signal can be a good solution to the new energy grid process to the new power system in the electronic type of intelligent equipment electromagnetic interference problem, composed of a new power system and the development of smart grid, as shown in Figure 14, for the new power system structure diagram.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material. Further inquiries can be directed to the corresponding author.

Author contributions

The individual contributions of the authors are as follows: data curation, GY; formal analysis, YC; methodology, FZ; supervision, SZ; writing (original draft), YZ. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

Authors GY, FZ, SZ, and YC were employed by Power China Hubei Electric Engineering Co. Ltd. Author YZ was employed by State Grid Hefei Power Supply Company. All authors declare that

the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 19 August 2022

ACCEPTED 06 September 2022

PUBLISHED 21 September 2022

CITATION

Li Y, Lou J, Sun K and Li K-J (2022),
Source-grid-load-storage interactive
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distribution network.
Front. Energy Res. 10:1023474.
doi: 10.3389/fenrg.2022.1023474

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Source-grid-load-storage interactive power quality characteristic of active distribution network

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Source-grid-load-storage has represented an interactive characteristic in the active distribution network (ADN). Moreover, power electronic devices have been widely used for source-grid-load-storage with the rapid development of power electronics technology. In this condition, the large-scale distributed source may cause voltage quality degradation, while the application of large-scale power electronics equipment may also lead to serious harmonic distortion. Power quality has become one of the most important issues in the development of ADN. In this paper, the source-grid-load-storage interactive power quality characteristic of the ADN is analyzed. Firstly, considering the source-grid-load-storage interaction in ADN, the voltage deviation and fluctuation are analyzed and the degrees are further quantified. Then, the source-load-storage harmonic models for the power electronic components are built, which is the basis for harmonic analysis. Moreover, the decoupled harmonic power flow algorithm for ADN is proposed to analyze the system harmonic distributions. Finally, considering the location and capacity of photovoltaic and energy storage, the interaction and power quality are analyzed in the IEEE 33-bus distribution system. With the access of energy storage, more than 20% of the voltage deviation and more than 6% of the voltage fluctuation caused by photovoltaics are effectively suppressed, while the harmonic distortion may be further increased.

KEYWORDS

distribution network, power quality, distributed energy resource, energy storage, voltage analysis, harmonic modeling

1 Introduction

With the change of energy structure in the distribution network, the source-grid-load-storage represents an obviously interactive characteristic. Moreover, the interaction is gradually enhanced with the development of flexible load (Hungerford et al., 2019), distributed energy resource (Quadri et al., 2018), and energy storage (ES) technology (Rahman et al., 2020). When the large-scale integration of distributed photovoltaic (PV) generation and energy storage are integrated into the distribution network, the whole distribution system has gradually developed into an active distribution network (ADN)

(Davarzani et al., 2021), (Yi et al., 2020), (Bastami et al., 2021), which not only results in voltage over range and fluctuation but also causes the change of system power flow and voltage distribution (Li et al., 2021).

The distribution network usually adopts the radial structure, with power flowing from the power source to the load in a single direction. However, the distributed PV feeds power into the active distribution system, increasing the bus voltage and even changing the power flow direction (Cavana et al., 2021), (Lin et al., 2021). Moreover, affected by the external environment and dispatch demand, the output of distributed energy resources presents time-varying and intermittent characteristics (Sun et al., 2021a), which can lead to bus voltage fluctuations. In this condition, the energy storage technology is developed due to the flexible power regulation ability, and it can provide an effective solution to the bus voltage over limit and fluctuation. Previous researches have done lots of beneficial studies on the coordination of distributed PV, load, and ES. A predictive power control scheme was proposed by (Shan et al., 2019) to control and coordinate the grid-connected PV systems with energy storage systems, which can maintain stable voltage and frequency and improve the power factor. In order to improve the stability of the distribution system, the coordination control strategy for residential load and distributed PV was proposed by (Cheng et al., 2020). Based on the communication framework, the distributed control strategy is developed by (Yu et al., 2021) to optimally coordinate the energy storage and regulate the system voltage.

In addition, with the rapid development of power electronics technology in different aspects of power systems (Xiao et al., 2021), (Sun et al., 2020a), power electronic devices have been widely used for the source-grid-load-storage (Kettner et al., 2021), (Ebrahimzadeh et al., 2019). In the active distribution network, the nonlinear loads represented by user appliances are emerging (Sun et al., 2020b), renewable energy generation represented by photovoltaic is gradually accessed (Gao et al., 2021), and the energy storage also needs the AC/DC conversion with power electronic equipment, which affects the system harmonic condition (Ghofrani et al., 2013). Thus, the AND harmonic distortion issue has attracted worldwide attention (Božiček et al., 2018). Severe harmonic contents will result in various problems in the AND, including power quality reduction, power loss increment, the equipment aging acceleration, etc., which affect the safe and economic operation of the power system (Kwon et al., 2016).

Based on the harmonic generation characteristics, the harmonic power flow can obtain the harmonic distributions in the distribution network (Cristaldi and Ferrero, 1995), (Šošić et al., 2015), which is one of the most effective methods to analyze harmonic distortion (Duan et al., 1996). Also, the interaction of source-grid-load-storage may change the operating state and then affect the harmonic generation (Xie et al., 2020). To date, harmonic power flow analysis mainly contains the time-domain simulation method, unified iterative method, fundamental and harmonic decoupled method, and so on. However, the time-domain simulation method has high computational complexity and

cannot reflect the harmonic generation mechanism. The unified iterative method is highly susceptible to convergence difficulties in iterative solving with the Newton-Raphson method. The decoupled method has been widely used due to the easier calculation process and good accuracy (Sun et al., 2007), (Xie and Sun, 2022). The modification procedures to customize the network component models in MATPOWER were presented in (Yang and Adinda, 2021), which can be used for the harmonic power flow study. Based on the field data, a harmonic power flow method was proposed by (Xie et al., 2022), which can evaluate and mitigate the random and time-varying harmonics.

As the installed capacity of distributed PV continues to rise, the operation of the traditional distribution network has changed. In the active distribution network, the power quality problems including voltage over range and serious harmonic distortion are getting worse (Campanhol et al., 2018). With the enhanced source-grid-load-storage interaction, the power quality issues caused by the large-scale distributed PV integration cannot be ignored. Therefore, this paper investigates the generation and influence of power quality problems with source-grid-load-storage interaction. The contributions are summarized as follows.

- 1 The influence on voltage is analyzed considering source-grid-load-storage interaction, the voltage deviation and fluctuation are analyzed and the degrees are quantified according to the typical structure of the active distribution network.
- 2 The frequency-domain harmonic models for the key power electronic components in the distribution network are built based on the frequency transfer matrix, which provides the basis for harmonic power flow calculation and analysis.
- 3 The decoupled harmonic power flow algorithm for the distribution network is proposed to analyze the system harmonic distributions. The interaction of source-grid-load-storage is analyzed based on the proposed harmonic power flow algorithm.

In the following, Section 2 analyzes the influence on voltage deviation and fluctuation with source-grid-load-storage interaction. Section 3 builds the harmonic models for distributed source, electrical load, and energy storage. Section 4 develops the harmonic power flow algorithm based on the harmonic model. Case studies and the results to show the source-grid-load-storage interactive influence are performed in Sections 5, 6 summarizes the conclusions of the paper.

2 Source-grid-load-storage interactive voltage influence analysis

The voltage deviation and fluctuation of the distribution network may be affected by the distributed PV and ES. When

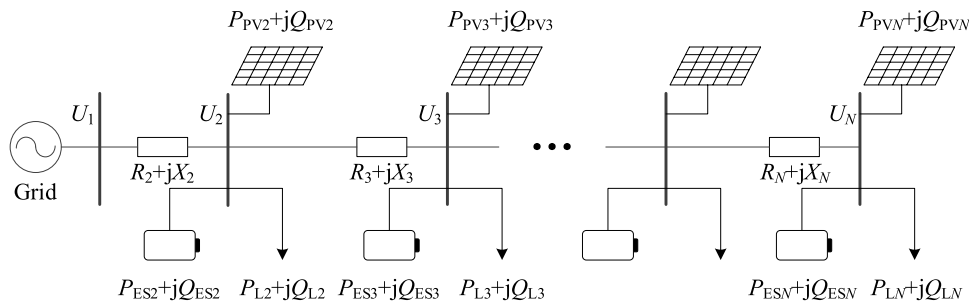


FIGURE 1
Structure of distribution network with the single feeder.

these components are connected to the distribution network reasonably, it can improve the distribution grid voltage distribution to a certain extent. However, unreasonable distribution of the source, load, and energy storage will change the system power flow and lead to voltage quality deterioration. To clarify the influence of integration of distributed PV and ES, the interaction of source-grid-load-storage of the distribution network is analyzed in this section.

2.1 Voltage deviation analysis

The structure of the distribution network with one single feeder is shown in Figure 1. In the figure, Bus 1 is the generator node, and the other buses are load nodes. The total number of buses of the distribution network is N , and U_n is the voltage of the n th bus. Each load node may be integrated with distributed PV generation and energy storage. p_{Ln} and Q_{Ln} are respectively the active and reactive powers of electrical load connected to the n th bus, P_{PVn} and Q_{PVn} are respectively the active and reactive powers of distributed PV generation connected to the n th bus, and P_{ESn} and Q_{ESn} are respectively the active and reactive powers of ES connected to the n th bus. R_n and X_n are respectively the resistance and reactance of the n th branch.

The power flow direction to the bus is set as positive, and that from the bus is set as negative. Generally, both the distributed PV and ES will not generate reactive power. Meanwhile, in order to improve the voltage quality of the distribution network, the energy storage is charged when the output of distributed PV is relatively large.

Considering the single distributed PV and single energy storage are connected to the m th bus, the total apparent power in Bus m is given as follows,

$$S_m = \left(\sum_{i=m}^N P_{Li} - P_{PVm} + P_{ESm} \right) + j \sum_{i=m}^N Q_{Li} \quad (1)$$

Assuming that the nominal voltage of the distribution network is U_{Nom} , the voltage difference between Bus $m-1$ and Bus m can be derived as follows,

$$dU_m = U_{m-1} - U_m = - \frac{R_m \left(\sum_{i=m}^N P_{Li} - P_{PVm} + P_{ESm} \right) + X_m \sum_{i=m}^N Q_{Li}}{U_{Nom}} \quad (2)$$

Then, the voltage difference between Bus 1 and Bus m can be obtained as follows,

$$\Delta U_m = \sum_{k=2}^m \frac{R_k \left(\sum_{i=k}^N P_{Li} - P_{PVm} + P_{ESm} \right) + X_k \sum_{i=k}^N Q_{Li}}{U_{Nom}} \quad (3)$$

where $R_k + jX_k$ is the equivalent impedance of the k th branch in the distribution network.

Meanwhile, the voltage of Bus m can be calculated as follows,

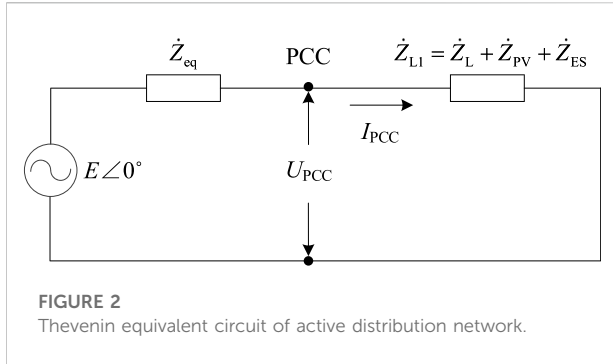
$$U_m = U_1 - \sum_{k=2}^m \frac{R_k \left(\sum_{i=k}^N P_{Li} - P_{PVm} + P_{ESm} \right) + X_k \sum_{i=k}^N Q_{Li}}{U_{Nom}} \quad (4)$$

where U_1 is the voltage of the generator node (Bus 1).

When there is no grid-connected PV generation, the voltage gradually decreases from the beginning of the feeder. The integration of distributed PV will increase the node voltage, and the larger the PV generation capacity, the greater the impact on the bus voltage. When the capacity of PV generation is relatively large, the voltage of the grid-connected bus will be larger than the other buses, changing the original monotonicity of the distribution network voltage distribution. The condition of monotonicity change is,

$$R_m P_{PVm} > R_m \sum_{i=m}^N P_{Li} + R_m P_{ESm} + X_m \sum_{i=m}^N Q_{Li} \quad (5)$$

In the case of multiple distributed pVs integration, the monotonicity of the voltage distribution will not be changed when the electrical load power is larger than the grid-connected



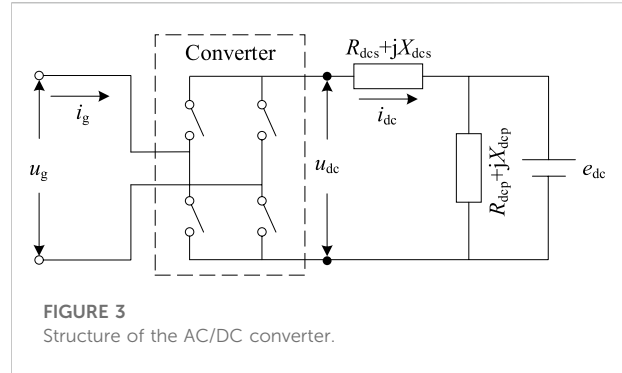
PV capacity in every bus. In the contrast, the monotonicity of the voltage distribution will change to the increasing trend when the electrical load power is smaller than the grid-connected PV capacity. In this way, active power controlling devices and reactive power compensation devices have been widely employed in the power system (Sun et al., 2021b). Moreover, the integration of ES will improve the voltage quality due to its bidirectional power flow characteristic. In this way, all voltages in each bus can be controlled in the acceptable range by adjusting the charging or discharging power.

From the above equations, it can be seen that the distributed PV generation may cause the voltage over range since the capability of PV generation is generally several times larger than the electrical load consumption. Also, the voltage deviation can be reduced by adjusting the active power of energy storage. Therefore, the voltage quality can be improved with the collaborative control of source-grid-load-storage.

2.2 Voltage fluctuation analysis

Considering the integration of distributed PV and ES, the Thevenin equivalent circuit of the active distribution network is shown in Figure 2. In this circuit, $E\angle 0^\circ$ represents the power supply voltage and $\dot{Z}_{eq}$ is the equivalent impedance of the grid side. $\dot{Z}_{L1}$ is the equivalent impedance of the load side, which contains the load equivalent impedance $\dot{Z}_L$, the source equivalent impedance $\dot{Z}_{PV}$, and the storage equivalent impedance $\dot{Z}_{ES}$. The voltage at the point of common coupling (PCC) is analyzed to reflect the source-grid-load-storage interactive voltage fluctuation.

The voltage at the PCC may fluctuate with the integration of distributed PV generation and energy storage in the distribution network, and the fluctuation can be reflected by the current change $\Delta I_{PCC}\angle\theta$. According to the consumption characteristics of electrical load and the charging feature of energy storage, the powers of load and storage will not change frequently resulting in voltage fluctuations. However, the voltage may fluctuate due to random and intermittent characteristics of PV output.



Consequently, the current change $\Delta I_{PCC}\angle\theta$ can be considered to be caused by PV output fluctuation ΔS_{PV} .

Based on the equivalent circuit, the voltage fluctuation change value ΔU_{PCC} at the PCC can be obtained as follows,

$$\begin{aligned}\Delta U_{PCC} &= Z_{eq}(\cos\varphi + j\sin\varphi) \cdot \Delta I_{PCC}(\cos\theta + j\sin\theta) \\ &= \frac{Z_{eq}\Delta S_{PV}}{U_{PCC}}[\cos(\varphi + \theta) + j\sin(\varphi + \theta)]\end{aligned}\quad (6)$$

where φ is the equivalent impedance angle of the grid side. U_{PCC} is voltage magnitude at the PCC. Thus, the voltage fluctuation can be represented by the change value ΔU_{PCC} . According to the equation, it can be seen that the degree of voltage fluctuation will be affected by multiple factors, including the PV output variation, the distribution network equivalent impedance, etc.

In these factors, the output variation of grid-connected PV generation has a direct impact on voltage fluctuation. When the weather changes rapidly, the system voltage will fluctuate significantly. Meanwhile, the distribution network equivalent impedance is related to the short-circuit capacity of the system. When distributed PV is integrated into the low-voltage distribution network, voltage fluctuation will be more obvious due to the relatively small short-circuit capacity of the low-voltage distribution network.

3 Source-load-storage harmonic characteristic analysis

3.1 Switching characteristic analysis

The topology of the commonly used AC/DC converter in distribution systems is shown in Figure 3. The single-phase converter is taken as an example in the paper. In this figure, u_g and i_g are the supply voltage and current in the grid side, respectively. u_{dc} and i_{dc} are the DC voltage and current, respectively. E_{dc} is the DC voltage source. $R_{dcs} + jX_{dcs}$ and $R_{dcp} + jX_{dcp}$ are respectively the equivalent DC series load and DC parallel load.

The converter switching behavior can be modeled as a frequency transfer matrix, and the matrix can be derived from the Fourier series coefficients of the switching function that describes the turn-on and turn-off states. Due to the differences in the power electronic converter devices used for source-load storage, there are differences in the form of their switching function expressions.

Distributed PV generally uses insulated gate bipolar transistor (IGBT) based converter devices with pulse width modulation (PWM) control for AC/DC conversion. The electrical loads may adopt different types of converters due to differences in the type of appliances. The diode-based three-phase uncontrolled rectifier circuit is used for AC/DC conversion, and the thyristor-based three-phase bridge rectifier circuit is employed for power regulating. Similar to the electrical load, the AC front-end of the energy storage converter generally uses the diode-based converter or the thyristor-based converter for power charging/discharging.

In the case of the diode-based uncontrolled converter, the switching function is described as,

$$S(t) = \frac{2\sqrt{3}}{\pi} \sum_{h=1}^{+\infty} \frac{(-1)^{(h-1)/2}}{h} \cos h\omega t \quad (7)$$

where h is the harmonic order. ω is the angular frequency of the fundamental wave.

Different from the uncontrolled converter, the thyristor-based converter needs to consider the controlled switching angle, which is measured with respect to the peak of DC voltage. The switching function for the thyristor-controlled converter is described as,

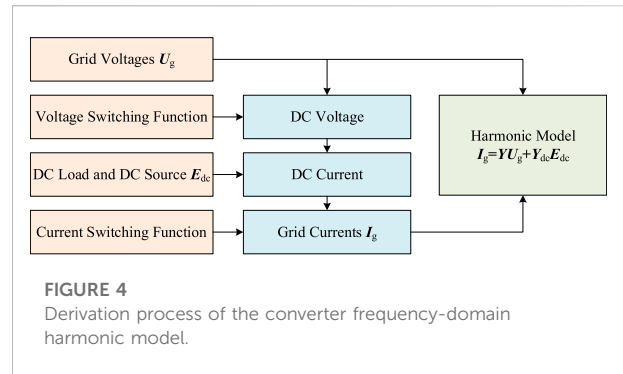
$$S(t) = \frac{2\sqrt{3}}{\pi} \sum_{h=1}^{+\infty} \frac{(-1)^{(h-1)/2}}{h} \cos h(\omega t - \alpha) \quad (8)$$

In the case of the PWM-controlled converter, the switching function is described based on the Bessel function $J()$. The switching function is related to the modulation degree M , and the specific expression is as follows,

$$S(t) = \frac{M}{2} \cos \omega t + \frac{4M}{\pi} \sum_{m=1}^{+\infty} \frac{1}{m} J_n\left(\frac{\pi}{2}mM\right) \sin \frac{(m+h)\pi}{2} \cos(h\omega t + m\omega_C t) \quad (9)$$

where ω_C is the angular frequency of the modulator wave.

According to the switching functions, the diode-based converter and the thyristor-based converter may generate low-frequency harmonic contents. While the IGBT-based converter mainly generates the high-frequency harmonic contents, since the modulator frequency is relatively high. As a result, the harmonic models of different types of converters including DER, electrical load, and energy storage can be established respectively. Also, the converter model can clarify the



coupling relationship between the harmonic voltage and harmonic current in the AC side.

3.2 Frequency-domain harmonic modeling

According to the modulation theory (Esparza et al., 2019), the current and voltage waveforms can also be represented by the current and voltage switching functions with the sine/cosine function. The DC voltage can be obtained by modulating the AC voltage through the turn-on and turn-off of the power electronic device, and the AC current can be obtained by modulating the DC current through the turn-on and turn-off of the power electronic device. The voltage and current relationship between the AC and DC sides can be expressed as,

$$u_{dc}(t) = S(t) \cdot u_g(t) \quad (10)$$

$$i_g(t) = S(t) \cdot i_{dc}(t) \quad (11)$$

where $S(t)$ is the time-varying switching function. $u_g(t)$ is the time-varying grid voltage, and $i_g(t)$ is the time-varying grid current. Ideally, the voltage switching function and the current switching function are the same. Since any stable periodic signal can be expressed as the Fourier series form (Sun et al., 2022), (Sun et al., 2021c), the time-domain variables can be transformed into the frequency-domain form as follows,

$$u_g(t) = \sum_{h=1}^H \sqrt{2} U_{gh} \cos(h\omega t + \varphi_{gh}) \quad (12)$$

$$i_{dc}(t) = I_{dc} + \sum_{h=1}^H \sqrt{2} I_{dch} \cos(h\omega t + \varphi_{dch}) \quad (13)$$

where h is the harmonic order, and H is the considered highest harmonic order. U_{gh} and φ_{gh} represent the magnitude and phase angle of the h th harmonic voltage in the grid side. I_{dc} is the DC current. I_{dch} and φ_{dch} denote the magnitude and phase angle of the h th harmonic current in the DC side.

On this basis, the frequency-domain harmonic model of the converter can be established, and the derivation process of this model is provided in Figure 4. In this model, $\mathbf{Y}$ is the harmonic admittance matrix characterizing the relationship between voltage and current in the AC side, and $\mathbf{Y}_{dc}$ is the harmonic admittance matrix representing the relationship between DC voltage and AC current.

According to the established harmonic model, it can be seen that the elements of the harmonic admittance matrix are independent of the harmonic components in the supply voltage, which can be used as the basic model for harmonic power flow calculation and accuracy improvement of harmonic analysis.

4 Source-grid-load-storage collaborative harmonic power flow

The decoupled method contains the calculation of the fundamental state and the calculation of the harmonic state. The input and output of the fundamental power flow equation are the fundamental nodal power and fundamental voltage or line flow, respectively.

4.1 Fundamental power flow analysis

The fundamental power flow of the whole distribution network can be calculated based on the Newton-Raphson method. For the Bus i in the distribution network, the fundamental power flow is based on the power differences ΔP_i and ΔQ_i ,

$$\begin{aligned}\Delta P_i &= P_i - U_i \sum_{j \in i} U_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\ \Delta Q_i &= Q_i - U_i \sum_{j \in i} U_j (G_{ij} \sin \theta_{ij} + B_{ij} \cos \theta_{ij})\end{aligned}\quad (14)$$

where P_i and Q_i are the active and reactive powers of bus i , respectively. U_i and U_j are the magnitudes of voltages of Buses i and j . G_{ij} and B_{ij} are the conductance and susceptance of the branch between Buses i and j , respectively. θ_{ij} is the phase difference of voltage between Buses i and j .

Based on the active power difference ΔP and reactive power difference ΔQ , the modified equation of Newton-Raphson method is as follows,

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = - \begin{bmatrix} \frac{\partial \Delta P}{\partial \theta} & \frac{\partial \Delta P}{\partial U} \\ \frac{\partial \Delta Q}{\partial \theta} & \frac{\partial \Delta Q}{\partial U} \end{bmatrix} \begin{bmatrix} \Delta \theta \\ \Delta U/U \end{bmatrix}\quad (15)$$

where U and θ are respectively the phase angle and magnitude of the voltage. Then, the value of U_i , U_j and θ_{ij} can be revised based on the phase angle difference $\Delta \theta$ and ΔU . The above process

needs to be iterated until one of the conditions in Eqs. (16), (17) is met.

$$\max(\Delta P, \Delta Q) \leq \varepsilon_1 \quad (16)$$

$$\max(\Delta V, \Delta \theta) \leq \varepsilon_2 \quad (17)$$

where ε_1 and ε_2 are thresholds for iteration termination. On this basis, the fundamental power flow can be calculated for the distribution network.

4.2 Harmonic power flow analysis

Considering the harmonic voltage is far less than the fundamental voltage in a real system, the calculation of fundamental and harmonic power flows can be considered independent of each other. Thus, the decoupled harmonic power flow is employed in the paper.

From the source-load-storage harmonic analysis, all types of components in the active distribution network may generate harmonics. Thus, there may be more than one harmonic source existing at the same time, which are distributed in different buses of the power system. The harmonic model of the source-load-storage can be represented as follows,

$$\begin{bmatrix} I^3 \\ I^5 \\ I^7 \\ \vdots \\ I^H \end{bmatrix} = \begin{bmatrix} I^{s3} \\ I^{s5} \\ I^{s7} \\ \vdots \\ I^{sH} \end{bmatrix} + \begin{bmatrix} Y^{3,3} & Y^{3,5} & Y^{3,7} & \dots & Y^{3,H} \\ Y^{5,3} & Y^{5,5} & Y^{5,7} & \dots & Y^{5,H} \\ Y^{7,3} & Y^{7,5} & Y^{7,7} & \dots & Y^{7,H} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Y^{H,3} & Y^{H,5} & Y^{H,7} & \dots & Y^{H,H} \end{bmatrix} \begin{bmatrix} U^3 \\ U^5 \\ U^7 \\ \vdots \\ U^H \end{bmatrix} \quad (18)$$

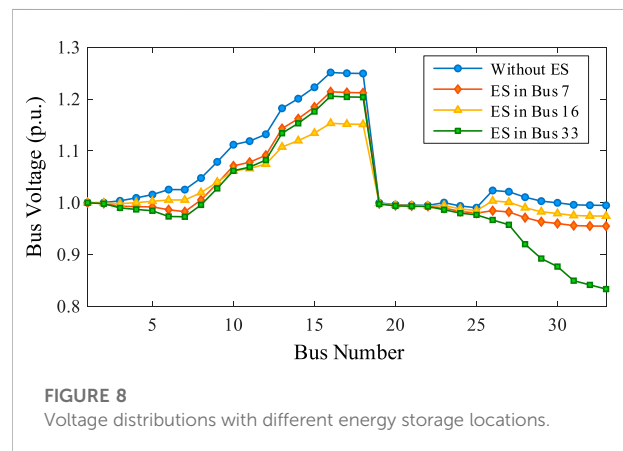
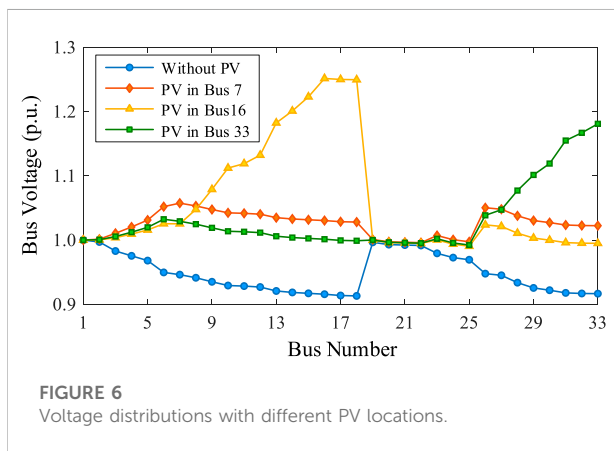
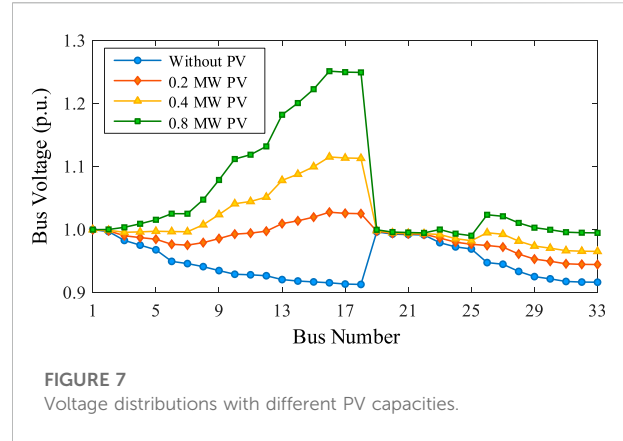
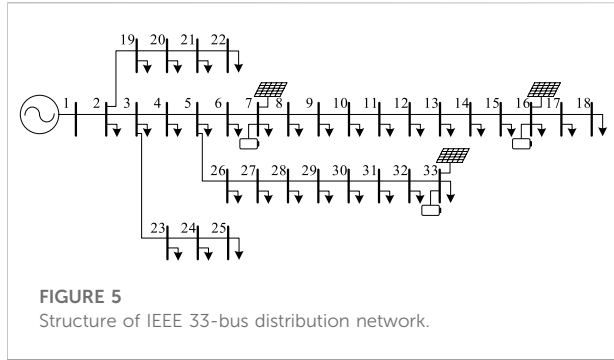
where I^h and U^h are the h th harmonic current and voltage, respectively. I^{sh} represents the h th harmonic of the current source. $Y^{h,h}$ denotes the admittance between h th harmonic voltage and h th harmonic current. Considering the self-coupling admittance is larger than the mutual-coupling admittance, the harmonic model can only consider the interaction between the harmonic voltage and current in the same order. Consequently, the h th harmonic in the source-load-storage harmonic model in the n th bus of the distribution network can be written as,

$$I_n^h = I_n^{sh} + Y_n^{h,h} U_n^h \quad (19)$$

Then, the harmonic model of the whole distribution network can be expressed as,

$$\mathbf{I}^h = \mathbf{I}^{sh} + \mathbf{Y}^h \mathbf{U}^h \quad (20)$$

where $\mathbf{I}^h$ and $\mathbf{U}^h$ are the matrices consisting of h th harmonic currents and voltages in each bus, respectively. $\mathbf{I}^{sh}$ is the matrix consisting of h th harmonic of the current source in each bus. $\mathbf{Y}^h$ is the matrix consisting of h th harmonic self-coupling admittance in each bus. Moreover, considering the structure of the distribution network, the matrix $\mathbf{I}^h$ can also be represented by,



$$\mathbf{I}^h = \mathbf{Y}^{Bh} \mathbf{U}^h \quad (21)$$

where $\mathbf{Y}^{Bh}$ denotes the node admittance matrix of the distribution network, which can be solved according to the system topology and branch admittances. Then, based on the Eqs. (20), (21), the matrix $\mathbf{U}^h$ consisting of h th harmonic voltages in each bus can be derived as,

$$\mathbf{U}^h = (\mathbf{Y}^{Bh} - \mathbf{Y}^h)^{-1} \mathbf{I}^{sh} \quad (22)$$

According to the h th harmonic voltage, the corresponding harmonic current can also be obtained. Therefore, the harmonic power flow can be calculated from the above analysis.

5 Case study

5.1 Source-grid-load-storage interactive voltage characteristic

To verify the influence of location and capacity on the network voltage, the impact of distributed PV generation and

energy storage are analyzed. The IEEE 33-bus distribution network proposed by (Baran and Wu, 1989) is employed to analyze the influence, and its structure is shown in Figure 5. In the IEEE 33-bus system, Bus 1 is the slack bus and the other buses are PQ nodes. Bus 7, Bus 16, and Bus 33 are selected as the PV and ES access locations.

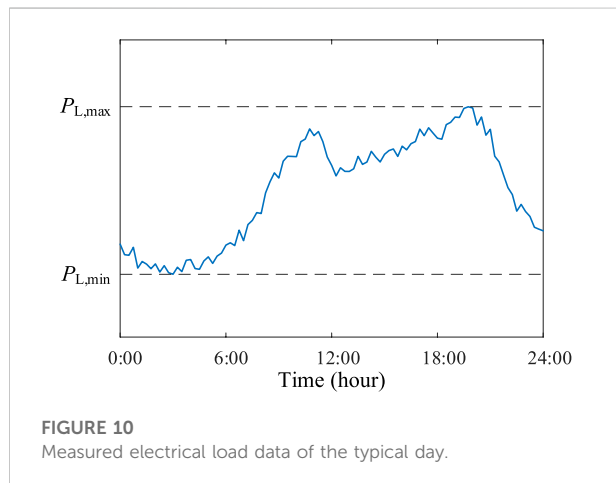
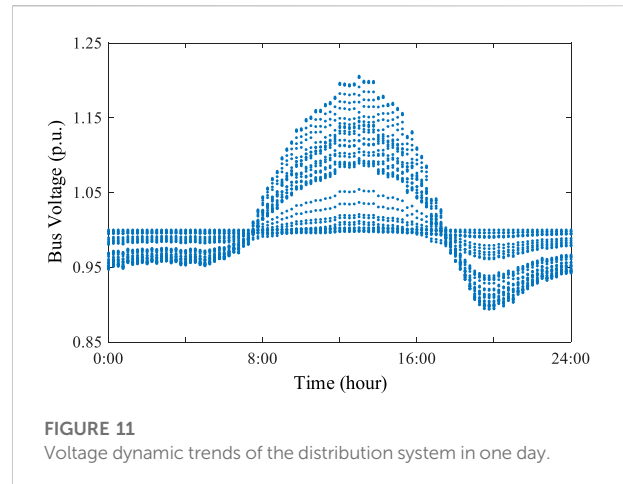
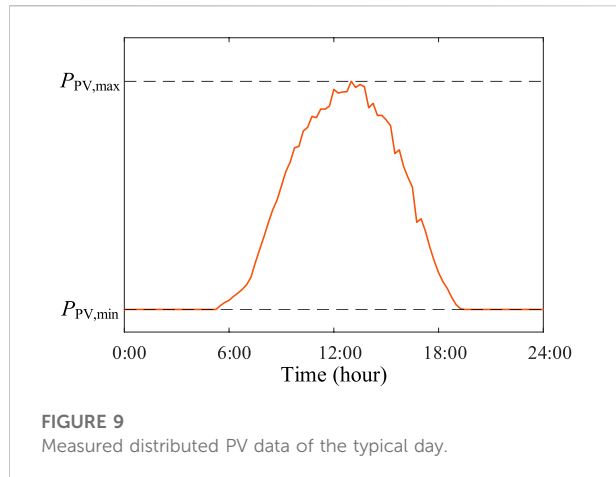
To quantitative the voltage deviation, the definition of voltage deviation ΔU is shown as follows,

$$\Delta U = \frac{U - U_{\text{Nom}}}{U_{\text{Nom}}} \times 100\% \quad (23)$$

where U is the voltage amplitude of system bus.

When the capability of distributed PV is 0.8 MW and there is no ES integration, the voltage distribution conditions under different PV access location is shown in Figure 6.

From the above figure, it can be seen that the integration of PV results in voltage improvement. When different buses are connected to the same photovoltaic capacity, the voltage variation trends of each bus are different. Therefore, the voltage sensitivity of each bus is different since the equivalent impedances are different in the grid side.



Then, the influence of distributed PV is analyzed. The comparisons of the voltage distributions without and with 0.2 MW, 0.4 MW, and 0.8 MW photovoltaic capacity integration in Bus 16 are shown in Figure 7. According to the results, the increase of distributed PV capacity has an obvious influence on the voltage, especially for the accessed location. Also, the voltage deviation may be over the limit that cannot be accepted when the PV capacity is relatively large.

In order to analyze the influence of energy storage, the voltage distributions are calculated with different ES access locations under the condition of 0.8 MW distributed PV integration in Bus 16. Similar to the PV locations, the energy storage is connected to Bus 7, Bus 16 and Bus 33, respectively. Assuming that the ES capability is 0.3 MW, the comparisons of the voltage distributions are shown in Figure 8.

From the results in Figure 8, the voltage magnitude can be mitigated with the energy storage integration. The voltage suppression is most effective when the distributed PV and ES

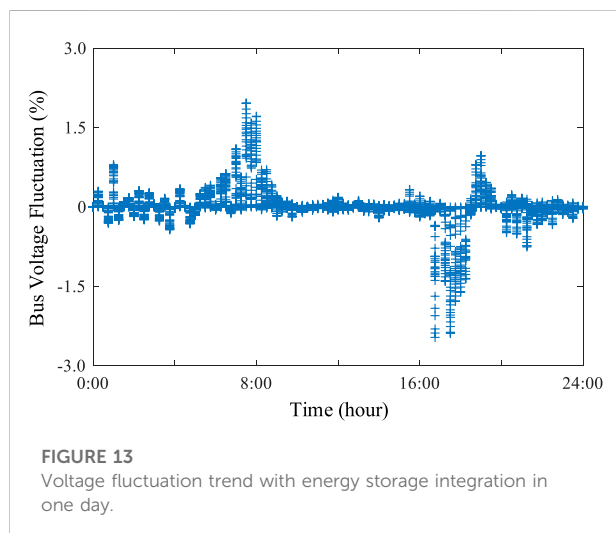
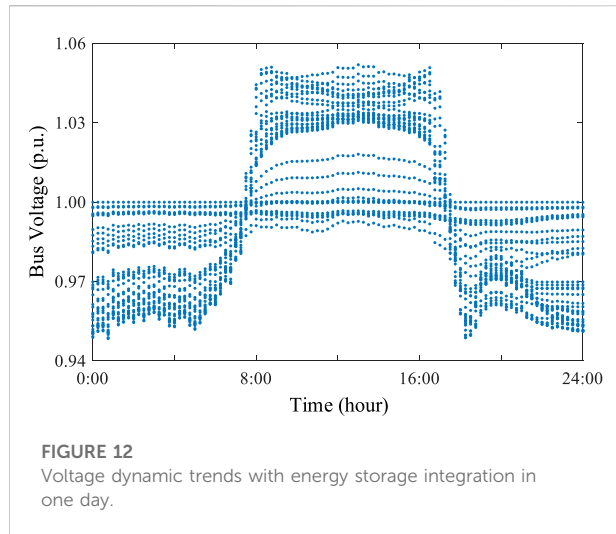
are connected to the same bus. Therefore, the energy storage can be connected to the node where the voltage rise is most pronounced to realize the power regulation effectively.

5.2 Source-grid-load-storage interactive dynamic characteristic

In order to analyze the source-grid-load-storage dynamic characteristic, the field-measured distributed photovoltaic and electrical load powers are employed, which are recorded every 15 min. The measured distributed PV data of the typical day is shown in Figure 9, and the typically measured load data is shown in Figure 10. In these figures, $P_{PV,max}$ and $P_{L,max}$ represent the maximum photovoltaic and load powers, respectively. $P_{PV,min}$ and $P_{L,min}$ are respectively the minimum photovoltaic and load powers, and the value of $P_{PV,min}$ is 0.

In the distribution network, the distributed PV generators with the maximum capability of 0.4 MW are connected to Bus 7, Bus 16 and Bus 33, and the PV output employs the power curve shown in Figure 9. The electrical load varies from 50% to 120%, which adopts the load power consumption curve in Figure 10. The voltage dynamic trend of each bus in the whole day can be obtained as shown in Figure 11. It can be seen that the system bus voltage exceeded the limit seriously at the time around 13:00, even up to about 1.2 p.u., due to the peak photovoltaic output. However, since the load consumption is relatively large, the bus voltage drops, and the voltage deviation increases significantly after 18:00.

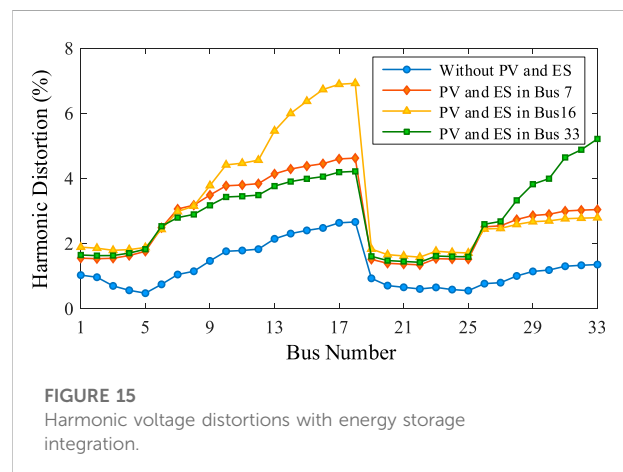
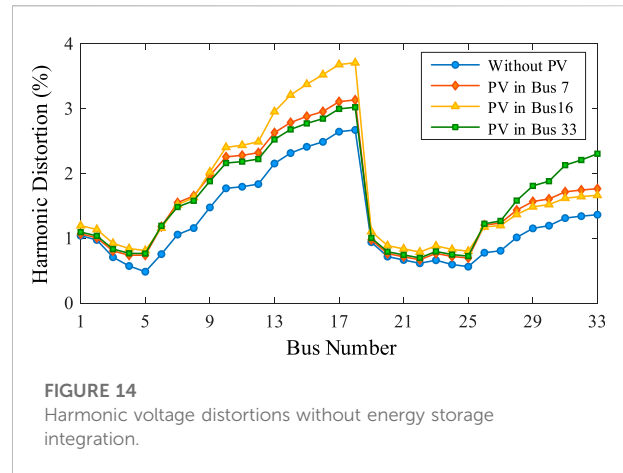
The energy storage is then employed in the distribution system to suppress the voltage, the location is the same as the distribution network. The maximum energy storage power $P_{ES,max}$ is set to 0.3 MW, and the minimum energy storage power $P_{PV,min}$ is 0. The ES control object is to retain the connected bus voltage within the range of 0.95 p.u. and



1.05 p.u. With the energy storage integration, the voltage dynamic trend of each bus in one day is shown in Figure 12.

From the results shown in Figure 12, it can be seen that the employment of energy storage suppresses the bus voltage in the period of large photovoltaic output. Also, the energy storage improves the voltage quality of the system in the case of heavy load. However, the voltage still maybe exceeds the control objective due to the limited capability of energy storage. Therefore, the optimization of energy storage capability also needs to be considered under source-grid-load-storage interaction.

Furthermore, the voltage fluctuations of each bus with energy storage integration are calculated as shown in Figure 13, and the voltage fluctuation is defined as follows,



$$d = \frac{\Delta U_d}{U_{\text{Nom}}} \times 100\% \quad (24)$$

where ΔU_d is the voltage difference between two RMS values. From Figure 13, it can be seen that the voltage fluctuations are generally less than 2.5%, which verifies the effectiveness of energy storage to improve voltage quality.

5.3 Source-grid-load-storage interactive harmonic characteristic

To analyze harmonic characteristics with source-grid-load-storage interaction, the 5th harmonic is taken as the example in

this section. Distributed PV generator with the capability of 0.4 MW is connected to Bus 7, Bus 16 and Bus 33, respectively. Meanwhile, the energy storage with the capability of 0.3 MW is also connected to Bus 7, Bus 16 and Bus 33, respectively. In the distribution network, 60% of load capability in each bus is set as the nonlinear rectifier-based load.

According to the converter operating characteristic, the current of the 5th harmonic source is set to 22.93% of the fundamental current for the energy storage and electrical load, and the current of the 5th harmonic source is set to 0.37% for the distributed PV. The comparisons of harmonic voltage contents in each bus with and without energy storage are shown in Figures 14, 15, respectively. For quantitative analysis of the harmonic voltage, the harmonic distortion of h th harmonic voltage HD^h is defined as follows,

$$HD^h = \frac{U^h}{U^1} \times 100\% \quad (25)$$

where U^h is the amplitude of h th harmonic voltage, and U^1 is the amplitude of the fundamental voltage.

As shown in these figures, it can be seen that the access locations of distributed PV and ES will affect the harmonic distributions. According to the comparison, although energy storage integration can improve the voltage quality of the distribution network, it will result in the harmonic content increasing with the source-grid-load-storage interaction. Therefore, the employment of energy storage needs to be fully considered for all kinds of power quality issues.

6 Conclusion

In terms of source-grid-load-storage interaction, the resulting voltage over limit and fluctuation issue is analyzed, and the harmonic distortion is calculated based on the proposed harmonic model. The following conclusions can be drawn as follows.

- 1 The influence on voltage is analyzed with source-grid-load-storage interaction, and the voltage deviation and fluctuation are qualified according to the typical structure of the active distribution network. The results show the effectiveness of energy storage on voltage suppression.
- 2 The frequency-domain harmonic models for key power electronics components are built based on the frequency transfer matrix, which provides the basis for harmonic power flow calculation and analysis in the active distribution network.

- 3 The interaction of source-grid-load-storage is analyzed based on the proposed harmonic power flow algorithm. With the integration of energy storage, the result shows that more than 20% of the voltage deviation and more than 6% of the voltage fluctuation are suppressed, while the harmonic distortion may be further increased.

Future research will focus on considering the source-load-storage uncertainties in the active distribution network. Moreover, the control strategy of distributed photovoltaic generation and energy storage is also an interesting topic with the interaction of source-grid-load-storage. With these topics, future research directions mainly include the operating state forecasting and probabilistic harmonic power flow calculation for the active distribution network (Le Nguyen, 1997).

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

YL: conceptualization, methodology, formal analysis, software, validation, and writing—review and editing. JL: conceptualization, writing—review and editing, and supervision. KS: methodology, validation, investigation, and data curation. KL: writing—review and editing, and supervision.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 11 August 2022

ACCEPTED 29 August 2022

PUBLISHED 26 September 2022

CITATION

Qin P, Ye J, Hu Q, Song P and Kang P
(2022), Deep reinforcement learning
based power system optimal carbon
emission flow.
Front. Energy Res. 10:1017128.
doi: 10.3389/fenrg.2022.1017128

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Deep reinforcement learning based power system optimal carbon emission flow

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Under the strain of global warming and the constant depletion of fossil energy supplies, the power system must pursue a mode of operation and development with minimal carbon emissions. There are methods to reduce carbon emissions on both the production and consumption sides, such as using renewable energy alternatives and aggregating distributed resources. However, the issue of how to reduce carbon emissions during the transmission of electricity is ignored. Consequently, the multi-objective optimal carbon emission flow (OCEF) is proposed, which takes into account not only the economic indices in the conventional optimal power flow (OPF) but also the reduction of unnecessary carbon emissions in the electricity transmission process, i.e., carbon emission flow losses (CEFL). This paper presents a deep reinforcement learning (DRL) based multi-objective OCEF solving method that handles the generator dispatching scheme by utilizing the current power system state parameters as known quantities. The case study on the IEEE-30 system demonstrates that the DRL-based OCEF solver is more effective, efficient, and stable than traditional methods.

KEYWORDS

deep learning, deep reinforcement learning, proximal policy optimization, carbon emission flow, optimal carbon emission flow

Introduction

To combat global warming and excessive consumption of fossil fuels, more and more renewable energy (RE) sources are being connected to the grid, resulting in a shift in the energy structure of the power system (Papaeftymiou and Dragoon, 2016). Based on ensuring the safety and dependability of the power system, many scholars have begun to focus on reducing the power system's carbon emissions.

On the production side of electricity, large-scale RE power plants are expanding at an alarming rate each year. According to statistics, the growth of renewable capacity is forecast to accelerate in the next 5 years, accounting for almost 95% of the increase in global power capacity through 2026 (IEA, 2021). Since a large number of RE with randomness and uncertainty will pose hidden dangers to the operation safety of the power grid (Bayindir et al., 2016; Alsaif, 2017; Impram et al., 2020), a portion of the thermal

power generator must be retained to maintain the system inertia. Consequently, how to improve the efficiency of traditional thermal power generators and reduce carbon emissions is also the focus of a great deal of research (Sharma et al., 2013; Sifat and Haseli, 2019; Seyam et al., 2020).

In addition, extensive research is being conducted to reduce the carbon emissions of the electricity consumption side of the power system. On the one hand, researchers hope to reduce the electricity that consumers obtain from the grid by employing distributed clean energy (Dhople, 2017; Gong et al., 2020; Chen et al., 2021). On the other hand, some research aggregates distributed resources to participate in the planning and dispatching of the power grid (Han et al., 2022; Sang et al., 2022; Zhang et al., 2022), allowing users to achieve more cost-effective and low-carbon electricity consumption goals through demand response.

In contrast, researchers have ignored how to reduce carbon emissions from the power system in the transmission line. Analyzing the distribution of carbon emissions in the power system is a prerequisite for investigating the reduction of carbon emissions during transmission. Some researchers view carbon emission as a virtual network flow dependent on active power flow (PF), analyzing the distribution characteristics of carbon emission flow (CEF) in power systems by analogy with active PF distribution (Kang et al., 2012). In (Kang et al., 2015), researchers propose a method for calculating CEF. However, most CEF analysis is conducted assuming a lossless network. Due to impedance in the transmission line, there will be a certain loss of active PF in the transmission process, and a portion of carbon emissions will not be transmitted to the electricity consumption side along with the active PF, resulting in the so-called carbon emissions flow loss (CEFL) that is unnecessary.

Furthermore, based on the optimal power flow (OPF) (Momoh et al., 1999a; Momoh et al., 1999b) and combined with the CEF analysis theory, researchers have proposed the optimal carbon emission flow (OCEF) model of the power system (Zhang et al., 2015; Cao et al., 2020), which takes into account the minimization of power generation cost and CEFL under the condition that the system's safety constraints are met. The OCEF problem is a complex nonconvex nonlinear programming problem, similar to the OPF problem. Traditionally, the OPF is typically solved on a large time scale to aid grid dispatchers in making day-ahead economic dispatching decisions. As more and more RE are connected to the grid, both the power production side and the power consumption side will demonstrate increasingly volatile fluctuations (Zhou et al., 2021). If the predicted value is used as an input to the OPF and the OCEF, the obtained results may deviate significantly from reality.

As a result, the input of the OCEF should be the real-time load value corresponding to the actual circumstance. This is more likely to obtain real-time OCEF in a relatively short time under the current state of the power system as the basis for economic low-carbon dispatching.

As stated previously, the OCEF problem is a notoriously challenging multi-objective nonconvex nonlinear programming problem. The conventional method for solving such problems involves linearization approximation and relaxation of constraint conditions. It is not easy to ensure that the obtained results can satisfy the optimal dispatching requirements of the power system because the computational complexity is high. The emergence of intelligent optimization algorithms, such as particle swarm optimization (Zhan et al., 2009) and genetic algorithm (Holland, 1992), solves the traditional method's dilemma. Their good solution space search ability can handle some optimization problems in discrete space. However, these traditional intelligent optimization algorithms require a large number of iterations to solve the OCEF problem, which is time-consuming. The solution's performance is positively correlated with the number of iterations. Therefore, it is difficult for these intelligent optimization algorithms to solve the OCEF in real-time.

Accordingly, the reinforcement learning (RL) (Kaelbling et al., 1996), which can actively obtain feedback from the environment and implement strategies in dynamic state space, has become a potent tool for many researchers to solve such optimization issues. A Markovian Decision Process (MDP) (Bellman, 1957) formalises the RL framework. Policy, reward, value, and agent are the four essential elements of RL. The agent needs to learn how to behave through trial-and-error interactions with a dynamic environment. During the learning process, the agent seeks a strategy that yields a high accumulated reward from its interactions with the environment (van Otterlo et al., 2012). The agent can then attain optimal control by selecting the actions with the highest value or the greatest expected cumulative reward.

RL has superior solution space search capabilities compared to conventional intelligent optimization algorithms. However, when the scale of the problem begins to grow and the action space and state space tend to be continuous, the training process for RL consumes too much computation. Although finding a solution closer to the optimal one may be possible, the time required to solve the problem is unacceptable. Consequently, in (Mnih et al., 2013), deep learning (DL) is combined with RL, and deep reinforcement learning (DRL) is proposed to address the issue of excessive computation. Utilizing the powerful function-fitting ability of deep neural networks (DNN), DRL aims to replace the value function and policy function in RL with DNNs. These networks' loss functions will be computed using Monte Carlo sampling estimation or the time difference equation. This method reduces the computational cost of RL while enhancing the ability to solve continuous action space and state space problems.

Using the Proximal Policy Optimization (PPO) algorithm (Schulman et al., 2017) in DRL and numerous performance improvement techniques, a real-time and efficient method for solving the OCEF is developed in this paper. The current power grid state parameters are input for a well-trained PPO agent. Obtaining the dispatching operation is possible through simple forward propagation. In addition, there is no need to repeat the

training process, as the solution procedure is extremely quick. This paper's contribution can be summarized as follows:

- 1) Based on the power system's CEF analysis, the influence of active power loss on CEF distribution in the grid is thoroughly accounted for. In order to modify the original carbon flow analysis, the CEFL is allocated to the generation side and the consumption side.
- 2) The OCEF problem is modelled as a process with continuous action space and state space MDP, making it more suitable for real-time power system dispatching.
- 3) The enhanced PPO is trained under the improved OCEF model, and a properly trained agent is deployed to solve the original problem precisely and expeditiously.

The following are the contents of this paper: *Methodology* describes the paper's model and analysis method; *Proposed DRL-based OCEF solutions* describes the OCEF solution framework based on the PPO algorithm; *Case study* is a case study; *Conclusion* contains the conclusion and prospect.

Methodology

Theory of carbon flow analysis in power system

The traditional method of calculating the total carbon emissions of the power system is to use the total macroscopic energy consumption over a long period. However, this method has certain hysteresis and is too imprecise to describe in detail the process of variation in the trend of carbon emissions over time. Also, it is challenging to identify the source of carbon emissions and evaluate carbon footprints. The theory of power system CEF analysis abstracts carbon emission into a virtual network flow that can flow in the grid alongside active PF. The theory analyses the distribution characteristics of CEF analogously to the distribution of active PF. In Table 1, the relationship between

the fundamental physical quantities in the CEF and PF, as well as their physical meanings, are defined.

For a power system with n_B nodes and n_G generators, without considering the active power loss, the NCI calculation formula is as follows:

$$\mathbf{E}_N = (\mathbf{P}_N - \mathbf{P}_B^T)^{-1} \mathbf{P}_G^T \mathbf{E}_G \quad (1)$$

where $\mathbf{E}_N$ is a n_B -dimensional NCI vector; $\mathbf{P}_N$ is the active power flux matrix of n_B nodes, which is a n_B -order diagonal matrix and the diagonal elements are the amount of active power flowing through each node; $\mathbf{P}_B$ is the branch PF distribution matrix. If there is at least one straight-through branch (transmission line) between nodes i and j ($i, j = 1, 2, \dots, n_B$) and the quantity of active PF from this branch (or branches) is p , then $\mathbf{P}_{Bij} = p$ and $\mathbf{P}_{Bji} = 0$. Otherwise $\mathbf{P}_{Bij} = \mathbf{P}_{Bji} = 0$; $\mathbf{P}_G$ is the power injection distribution matrix of size $n_G \times n_B$. If the k th generator is connected to the node j , and the power injected from the k th generator to node j is p , then $\mathbf{P}_{Gkj} = p$; $\mathbf{E}_G$ is a n_G -dimensional generator carbon emission intensity (CEI) vector, where the k th element represents the CEI of the k th generator set.

The isolated nodes should not be included in the matrix calculation in this study in order to avoid the singular matrix. A network's isolated node is defined as a node that is not adjacent to any other nodes.

Transmission loss allocation method based on the active power flow tracking

The power grid model is considered a lossless network in the preceding CEF calculation. In the actual power grid, however, this analysis method will cause errors. As a result, the existing lossy network should be converted to an equivalent lossless network. There is no doubt that electricity consumption is the root cause of electricity production, so consumers and producers should share network loss.

Based on the power flow tracking method in the power system (Power, 2017), this paper employs a network lossless equivalent method combining downstream tracking and

TABLE 1 THE basic physical quantities of CEF analysis.

Names	Unit	Physical meaning	Corresponding Physical Quantities in Power Flow Analysis of Power System
Branch CEF (BCEF)	kg	The cumulative amount of carbon emissions produced by the system at the power plant to maintain active power flow over a given period of time	Transmission power in branch
BCEF rate	kg/s	The amount of carbon emitted per unit time by the system at the power plant to maintain the active power flow	Active PF in branch
BCEF intensity	kg/kWh	BCEF per unit time with a unit active power flow	
Nodal carbon intensity (NCI)	kg/kWh	A unit of electricity consumed at the node corresponds to the carbon emissions of the power plant	

upstream tracking. The network loss is proportional to the additional load at nodes based on the original load amount. The network loss is equivalent to the extra load at generation nodes based on the power injected by the generator.

According to upstream tracking, let $\mathbf{P}^{(g)}$ be the active power flux vector of each node in the equivalent lossless network. $\mathbf{P}_{GN}$ is the n_B -dimensional vector that describes the active power output of generators received by each node. By introducing an upstream distribution matrix $\mathbf{A}_u$, the power balance expression of each node can be written as follows:

$$\mathbf{A}_u \mathbf{P}^{(g)} = \mathbf{P}_{GN} \quad (2)$$

$$[\mathbf{A}_u]_{ij} = \begin{cases} 1, & i = j \\ -|P_{j-i}|/P_j, & j \in U_i \\ 0, & \text{others} \end{cases} \quad (3)$$

where U_i is the set of upstream nodes of node i .

Since the network loss is relatively low, it can be assumed that the proportion of load in the active power flux of the node remains unchanged before and after the equivalence; hence, the equivalent load at node i is

$$|P_{Li}^{(g)}| = \frac{|P_{Li}^{(g)}|}{P_i^{(g)}} P_i^{(g)} \cong \frac{P_{Li}}{P_i} P_i^{(g)} \quad (4)$$

The network loss equivalent to the load node is

$$\Delta \mathbf{P}_L = \mathbf{P}_L^{(g)} - \mathbf{P}_L \quad (5)$$

where $\mathbf{P}_L^{(g)}$ is the equivalent nodal load vector, $\mathbf{P}_L$ is the nodal load vector before equivalence.

The process of equivalent network loss to the generation node by the downstream tracking method is similar to the above process. By introducing a downstream distribution matrix $\mathbf{A}_d$, the power balance expression of each node can be written as follows:

$$\mathbf{A}_d \mathbf{P}^{(g)} = \mathbf{P}_L \quad (6)$$

$$[\mathbf{A}_d]_{ij} = \begin{cases} 1, & i = j \\ -|P_{i-j}|/P_j, & j \in D_i \\ 0, & \text{others} \end{cases} \quad (7)$$

where D_i is the set of downstream nodes of node i .

Further, elements of the vector $\mathbf{P}_{GN}$ after equivalence is

$$|P_{GNi}^{(g)}| = \frac{|P_{GNi}^{(g)}|}{P_i^{(g)}} P_i^{(g)} \cong \frac{P_{GNi}}{P_i} P_i^{(g)} \quad (8)$$

The network loss equivalent to the generation node is

$$\Delta \mathbf{P}_G = \mathbf{P}_{GN} - \mathbf{P}_{GN}^{(g)} \quad (9)$$

The total network loss in the system is

$$Loss = \Delta \mathbf{P}_L = \Delta \mathbf{P}_G \quad (10)$$

As stated previously, both the generation side and the load side should share the transmission network loss. Consequently, the

allocation ratio $\beta \in (0, 1)$ is set to allocate a portion β of the total network loss to the generation side and a portion $1 - \beta$ to the load side, which can be expressed as follows:

$$\Delta \mathbf{P}_G' = \beta \Delta \mathbf{P}_G \quad (11)$$

$$\Delta \mathbf{P}_L' = (1 - \beta) \Delta \mathbf{P}_L \quad (12)$$

The allocation ratio β can be negotiated by power generation companies, electricity consumers and electricity retailers.

Problem formulation of power system optimal carbon emission flow

The CEFL of the network loss apportioned to the generation side can be directly calculated by multiplying the apportioned network loss by the generator's CEI. By analyzing the distribution characteristics of CEF in the power grid, the CEFL assigned to the load side can be determined.

The equivalent network loss of the load side can be related to the generator through the path of active power transmission by introducing the generator-to-node incidence matrix R_{U-N} . R_{U-N} can be calculated as follows:

$$R_{U-N} = [P_N (P_N - P_B^T)^{-1} P_G^T]^T \quad (13)$$

The size of the R_{U-N} is $K \times N$. After elements in R_{U-N} are normalized by the sum of all elements in the column, the element $\bar{R}_{U-Nij}$ in $\bar{R}_{U-N}$ represents the percentage of active power contribution of the i th generator to the load on node j . Further, the load side equivalent network loss traced to each generator can be calculated by the following formula:

$$\Delta \mathbf{P}_{G-L} = (\text{diag}(\Delta \mathbf{P}_L') \bar{R}_{U-N})^T \quad (14)$$

$\Delta \mathbf{P}_{G-L}$ is a matrix of size $K \times N$, where the element ΔP_{G-Lij} represents the part of the network loss shared by node j from the i th generator. Each row of the matrix is summed to obtain the n_G -dimensional vector $\Delta \mathbf{P}_{g-l}$. The element ΔP_{g-li} in this vector represents the active power contributed by the i th generator to the network loss allocated to all its associated nodes.

Finally, the total CEL F_{CEFL} in the power system can be calculated by the following formula:

$$F_{CEFL} = E_G^T (\Delta \mathbf{P}_G' + \Delta \mathbf{P}_{g-l}) \quad (15)$$

Based on the OPF problem, the OCEF problem is constructed by adding the objective of reducing unnecessary CEFL. The construction of the OCEF in the power system can be stated as follows:

$$\min. \quad C_G + F_{CEFL} \quad (16)$$

Subject to:

$$P_{gk}^{\min} \leq P_{gk} \leq P_{gk}^{\max}, \forall k \in G \quad (17)$$

$$Q_{gk}^{\min} \leq Q_{gk} \leq Q_{gk}^{\max}, \forall k \in G \quad (18)$$

$$V_k^{\min} \leq |V_k| \leq V_k^{\max}, \forall k \in N_b \quad (19)$$

$$|S_{lm}| \leq S_{lm}^{\max}, \forall (l, m) \in L \quad (20)$$

$$P_{gk} - P_{dk} = \sum_{l \in N_b(k)} \operatorname{Re}\{V_k(V_k^* - V_l^*)y_{kl}^*\} \quad (21)$$

$$Q_{gk} - Q_{dk} = \sum_{l \in N_b(k)} \operatorname{Im}\{V_k(V_k^* - V_l^*)y_{kl}^*\} \quad (22)$$

where G is a set composed of all generators in the system; P_{gk} is the active output of the k th generator; Q_{gk} is the reactive output of the k th generator; V_k is the voltage phasor of node k ; N_b is the set composed of all nodes in the system; S_{lm} is the power transmitted on the branch l - m ; L is the set of nodes connected by a transmission line. (21) and (22) describe the system power balance constraint.

Proximal policy optimization algorithm

This paper employs the PPO algorithm, which is effective, robust and generalizable. The PPO algorithm and the TRPO algorithm have essentially the same structure, both utilizing the policy gradient method for training, i.e., parameterising the strategy. The strategy is optimized by designing an objective function to measure the quality of the strategy and then maximizing this objective function using the gradient ascent method.

The objective function of PPO can be expressed as follows:

$$\max_{\theta} J(\theta) = E_{s_0}[V^{\pi_{\theta}}(s_0)] = E_{\pi_{\theta}}\left[\sum_{t=0}^{\infty} \gamma^t r(s_t, a_t)\right] \quad (23)$$

where θ is the parameter of random strategy π_{θ} ; π_{θ} is the probability function modelled by neural networks, which input is a certain state, and the output is the probability distribution of taking action in this state; s_t is the state at t th step; a_t is the action at t th step; γ is the discount coefficient; $r(s_t, a_t)$ is the return function; $V^{\pi_{\theta}}(\bullet)$ is the value function under the strategy π_{θ} .

The following formula calculates the gap between the objective functions under the old and new strategies:

$$J(\theta') - J(\theta) = E_{\pi_{\theta'}}\left[\sum_{t=0}^{\infty} \gamma^t [r(s_t, a_t) + \gamma V^{\pi_{\theta}}(s_{t+1}) - V^{\pi_{\theta}}(s_t)]\right] \quad (24)$$

By introducing the advantage function $A^{\pi_{\theta}}(s_t, a_t)$, (Eq. 24) can be rewritten as follows:

$$J(\theta') - J(\theta) = \frac{1}{1-\gamma} E_{s \sim \pi_{\theta'}, a \sim \pi_{\theta'}(\cdot|s)}[A^{\pi_{\theta}}(s, a)] \quad (25)$$

The advantage function can be calculated by generalized advantage estimation (GAE) (Schulman et al., 2018):

$$A^{\pi_{\theta}}(s_t, a_t) = \sum_{l=0}^{\infty} (\gamma \lambda)^l (r_t + \gamma V^{\pi_{\theta}}(s_{t+1}) - V^{\pi_{\theta}}(s_t)) \quad (26)$$

where $\lambda \in [0, 1]$ is the hyperparameter defined for computing the generalized advantage estimation.

Therefore, it is only necessary to find a new policy to let $E_{s \sim \pi_{\theta'}, a \sim \pi_{\theta'}(\cdot|s)}[A^{\pi_{\theta}}(s, a)]$, so that the monotonically increasing performance of the policy can be guaranteed.

Since the new strategy is unknown and must also be used for sampling, it is extremely challenging to solve the equation directly. Hence, if the change in state visit distribution between two policies is ignored and the old strategy's state distribution is adopted directly, after introducing importance sampling to process distribution of action, the optimization goal can be defined as:

$$L_{\theta}(\theta') = J(\theta) + \frac{1}{1-\gamma} E_{s \sim \pi_{\theta}, a \sim \pi_{\theta'}(\cdot|s)}[R(\theta) A^{\pi_{\theta}}(s, a)] \quad (27)$$

where the importance sampling is

$$R(\theta) = \frac{\pi_{\theta'}(a|s)}{\pi_{\theta}(a|s)} \quad (28)$$

PPO algorithm uses truncation to limit Kullback-Leibler (KL) divergence (Kullback and Leibler, 1951) between old and new policies, ensuring they are close enough and avoiding complex constrained problems. The objective function of optimization can be rewritten as follows:

$$\arg \max_{\theta'} E_{s \sim \pi_{\theta_k}, a \sim \pi_{\theta_k}(\cdot|s)}[\min(R(\theta) A^{\pi_{\theta_k}}(s, a), \operatorname{clip}(R(\theta), 1 - \epsilon, 1 + \epsilon) A^{\pi_{\theta_k}}(s, a))] \quad (29)$$

where, $\operatorname{clip}(x, l, r) = \max(\min(x, r), l)$ restricts x within $[l, r]$; ϵ is the hyperparameter to adjust the truncation range.

Proposed DRL-based OCEF solutions

The framework for handling the OCEF problem of the power system using the DRL-based solver proposed in this paper is depicted in Figure 1. The PPO agent is trained by interacting with a simulated power grid environment to discover the optimal strategy for various grid states. When constructing the OCEF solver with a well-trained agent, only forward propagation calculations are required to obtain the (approximate) OCEF in the current state.

State and action space

The agent receives the state variables provided by the simulated grid environment and then outputs corresponding actions to modify the current state of the grid in order to reduce power generation cost and CEFL. Therefore, the state should contain the key variables describing the grid's current state, which the agent can use to output the optimal action.

The state space and action space construction method used in this paper refer to (Zhou et al., 2021). The key variables to

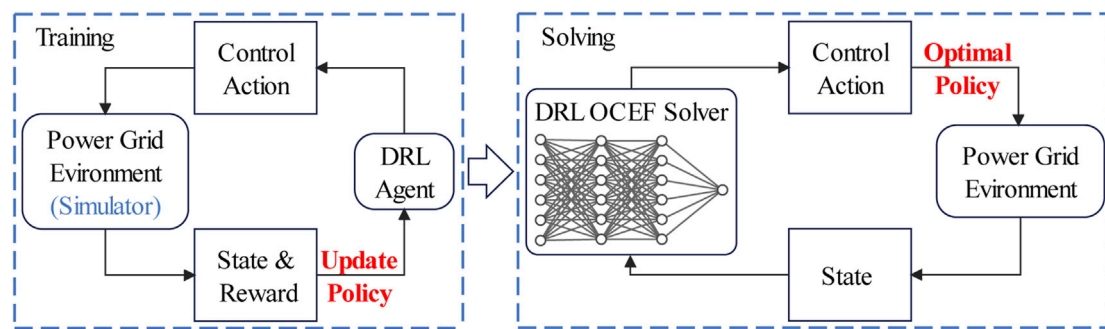


FIGURE 1
The DRL-based framework to solve the OCEF problem.

describe the power grid state are: active load P_d and reactive load Q_d of n_B nodes; amplitude $|Y|$ and phase angle $\angle Y$ of self-admittance of n_B nodes; the active power output P_g and the voltage V_g of the n_G generators. Thus, the state space is shown as follows:

$$\text{state} = [P_{d1} \sim P_{dn_B}, Q_{d1} \sim Q_{dn_B}, |Y_1| \sim |Y_{n_B}|, \angle Y_1 \sim \angle Y_{n_B}, P_{g1} \sim P_{gn_G}, V_{g1} \sim V_{gn_G}] \quad (30)$$

The action space, which contains active power output of generator adjustment value ΔP_g and voltage adjustment ΔV_g of n_G generators, is shown in the Formula 31:

$$\text{action} = [\Delta P_{g1} \sim \Delta P_{gn_G}, \Delta V_{g1} \sim \Delta V_{gn_G}] \quad (31)$$

The structure of policy network and value network

PPO utilizes two neural networks to fit the policy function and the value function, similar to the Actor-Critic algorithm. The policy network, which is the agent in the PPO algorithm, is responsible for generating actions according to the state. The value network generates the appropriate value based on the present state.

First, the primary portion of the policy network is constructed. Considering the power grid's topology, this paper divides the six state variables in the state space into generator state variable matrix sg of size $2 \times n_G$ and node state matrix sb of size $4 \times n_B$. Two convolutional layers are required to extract the matrices' information when two sets of state variable matrices are input into the policy network. There are 16 convolutional kernels of size 3×3 and a stride size of 1×1 for each of the two convolutional layers, whose parameters are identical. Using zero padding to fill the edges of the matrix guarantees that all state variable information will be sensed. Unlike a convolutional neural network that processes image input, this paper does not use

max-pooling to extract features from the convolutional layer's output to preserve all power grid state parameters.

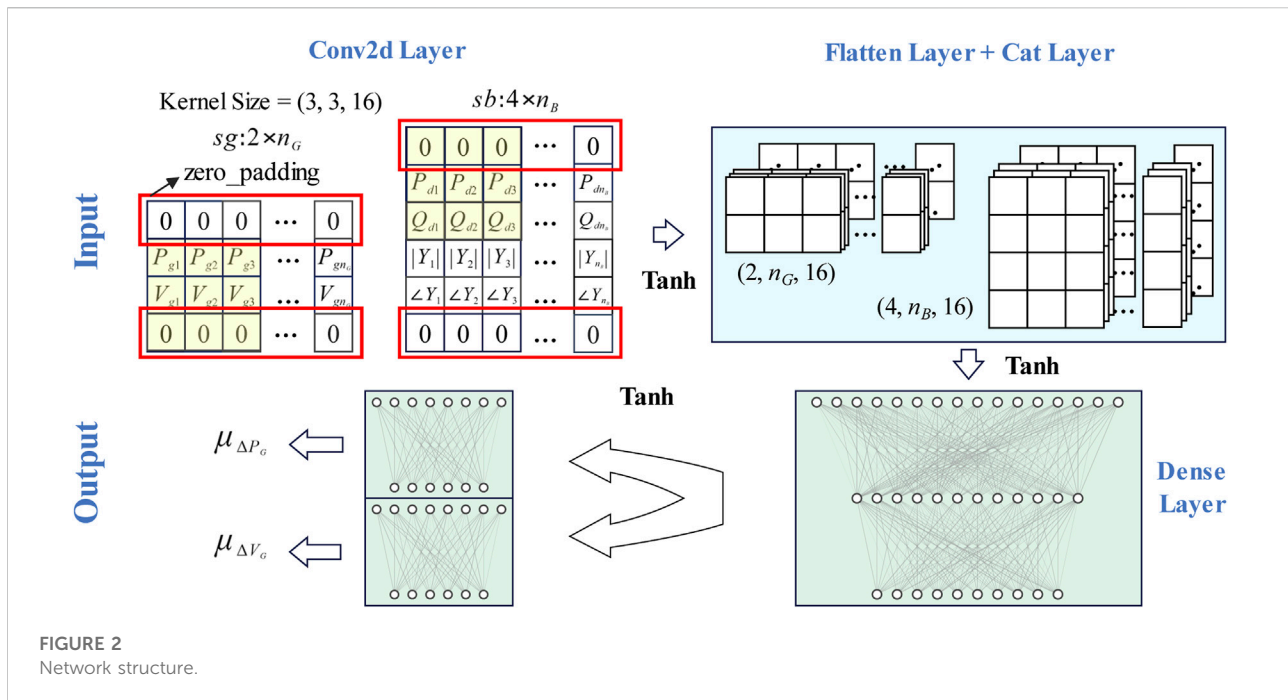
Second, the policy network is designed to generate actions in a particular way. PPO is a typical DRL algorithm with stochastic strategies. For discrete actions, the agent will directly generate the probability distribution of each action and make specific action decisions by random sampling based on the probability distribution generated for training. When the agent is used as a solver, it will always select the action with the highest probability and thus make the optimal decision. For continuous action in this paper, the agent generates the Gaussian distribution's mean and variance, which have the same degree of freedom of action. During training, the agent randomly sampled specific actions based on the Gaussian distribution. As a solver, it always selects the mean action value because the mean value is the action value with the maximum probability.

Third, select the activation function and construct the remaining policy network components. The policy network in this paper consists of two output layers. Using the Tanh function to activate the outputs will generate actionable means. The parameterization is used for variation to make the parameters trainable. The fully connected layer constructs all hidden layers in the policy network, and the layer norm is used to avoid the gradient vanishing problem. Figure 2 is a diagram illustrating the structure of the policy network.

The structure of the value network is comparable to that of the policy network, as its output is the value determined based on the current state. The size of the output layer only needs to be as large as the output value, so no additional details are required.

The hyper-parameters of the policy network and the value network are shown in Table 2.

The trainable parameters of the neural networks in both the policy network and the value network should be initialized with orthogonal initialization. The orthogonal initialization can further mitigate the problems of gradient disappearance and gradient explosion that can occur during the training process, thereby enhancing the training's stability.



Training process of PPO agents

In the DRL algorithm, agents gain experience by constantly interacting with the environment and ultimately acquire the optimal strategy to guide them to obtain the greatest cumulative reward. This study uses a PF solver to simulate the power grid environment. Figure 3 is The flowchart of the agent interacting with the simulated power grid environment.

In this process, the initial state $s_0=(sg_0, sb_0)$ is randomly generated by the function *env. reset()* according to the actual topology of the power grid. It is necessary to ensure that the system's initial state satisfies the operational constraints. At t th step, the agent detects the state s_t of the system from the simulated power grid environment, modifies the current state based on the action a_t specified by the strategy, and obtains the next state s_{t+1} . Additionally, the environment provides the agent with an immediate reward r_t for taking action a_t state s_t and a signal *done* indicating whether the termination state has been reached. The interaction process between the agent and the environment will continue until it is terminated. The above environment is defined as the function *env. step()*.

The immediate reward value for the current step is calculated according to (32), which is a piecewise function. When the PF solver in the environment diverges, the environment will feed back a large negative reward to the agent, causing the agent to avoid this situation in the future. If some constraints are not met, the agent will receive a negative reward proportional to the overlimit value of various variables. Agents will make fewer decisions that may lead to constraint violations if the reward is low. When the PF solver is

solvable, and there are no violation issues, the environment will give the appropriate reward based on the power generation cost and CEFL calculated from the current state. Agents will be encouraged to make decisions that reduce the cost of power generation and the CEFL by monetary incentives.

$$\text{reward} = \begin{cases} -5000, & \text{if PF solver is diverged} \\ R_{Pg_v} + R_{V_v} + R_{Br_v}, & \text{if there are constraints violations} \\ 2000 - C_G - 1000 \times F_{CEFL}, & \text{if feasible} \end{cases} \quad (32)$$

where R_{Pg_v} is the negative of the overlimit value of the active power output of generators; R_{V_v} is the negative of the overlimit value of nodes voltage; R_{Br_v} is the negative of the overlimit value of the power transmitted by the line. To calculate the positive reward, the coefficient of the CEFL value F_{CEFL} is set to be the same order of magnitude as the generation cost.

Although PPO belongs to the off-policy DRL algorithm, the interaction process can still utilize the replay buffer to save data. When the amount of data in the replay buffer reaches a predetermined threshold, the policy network and value network loss functions are calculated for propagation. At the beginning of the next interactive round, the data stored during the previous training round is cleared after the network parameters have been updated.

The loss function of the policy network is

$$L_{Actor} = -\min(R(\theta)_t A^{\pi_\theta}(s_t, a_t), \text{clip}(R(\theta)_t, 1 - \epsilon, 1 + \epsilon) A^{\pi_\theta}(s_t, a_t)) - \alpha H(\pi_\theta(\bullet|s_t)) \quad (33)$$

where α is the regularization coefficient; $H(\pi_\theta(\bullet|s_t))$ is the entropy of the current strategy. In information theory and

TABLE 2 The hyperparameters of the policy network and the value network.

Layers	Layer type	Hyper-parameter
Policy Net		
conv_gen_1	Conv2d	Kernels: 16, Size: 3×3 , Stride: 1×1
conv_node_1	Conv2d	Kernels: 16, Size: 3×3 , Stride: 1×1
hidden_1	Dense	Units: 1024
hidden_2	Dense	Units: 256
Value net		
conv_gen_2	Conv2d	Kernels: 16, Size: 3×3 , Stride: 1×1
conv_node_2	Conv2d	Kernels: 16, Size: 3×3 , Stride: 1×1
hidden_4	Dense	Units: 1024
hidden_5	Dense	Units: 256
hidden_6	Dense	Units: 64
output_3	Dense	Units: 1

probability statistics, entropy is used as a measure to describe the uncertainty of random variables. The greater the entropy, the more average the probability of each action selected by a strategy. $H(\pi_{\theta}(\bullet|s_t))$ is calculated as follows:

$$H(\pi_{\theta}(\bullet|s_t)) = E_{a_t \sim \pi_{\theta}} [-\log(\pi(a_t|s_t))] \quad (34)$$

The loss function of the value network is the advantage function obtained by GAE:

$$L_{Critic} = \hat{A}_t^{GAE}(\gamma, \lambda) = \sum_{l=0}^{\infty} (\gamma \lambda)^l \delta_{t+l}^V \quad (35)$$

Algorithm 1 shows in detail the training process of the PPO agent to solve the OCEF.

Algorithm 1. PPO training for solving the OCEF problem.

1. Initialization: the number of interactions between the agent and the environment during the whole training process *total_steps*, the maximum number of interactions *max_train_steps*, the number of interactions in the current training round *episode_steps*, the policy network *Actor*, the upper limit of the maximum number of interactions in a single training round *max_episode_steps*, the upper storage limit of replay buffer *batch_size*, the number of data stored in the replay buffer *replay_buffer_count*, the function that calculates losses from the data in the replay buffer and propagates them back *update*.

2. For *total_steps* in range(*max_train_steps*):

```

while not done:
    a ← Actor(sg, sb)
    sg, sb, r, done ← env.step(a)
    if done and episode_steps != max_episode_steps:
        d_w ← True
    else:
        d_w ← False
    if episode_steps == max_episode_steps:
        done ← True
        d_w ← False
    replay_buffer ← sg, sb, a, r, sg, sb, d_w, done
    sg, sb ← sg, sb_
    if replay_buffer_count == batch_size:
        update(replay_buffer)

```

Case study

The proposed method for solving the OCEF problem based on the DRL algorithm is tested on the IEEE-30 system. The system consists of six generators, 30 nodes and 41 lines. Python 3.7 and Pytorch 1.11.0 +

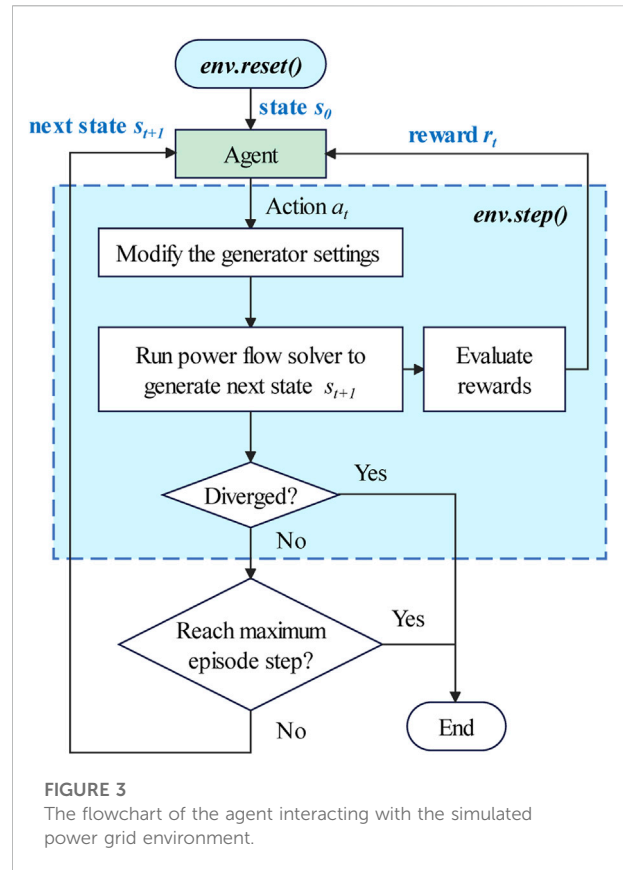


FIGURE 3 The flowchart of the agent interacting with the simulated power grid environment.

cu113 are used to build a simulation test platform. The power grid simulation environment is built with the PF solver in Pypower. Pypower is a Python platform port to the Matpower toolkit in Matlab.

The default initial grid parameters of the IEEE-30 system are as follows. The outputs of the generator and load on the node are shown in Table 3.

The power transmitted on each branch is shown in Table 4. The cost of generation is calculated as follows.

$$C_G = \sum_{k=1}^6 c_2 P_{gk}^2 + c_1 P_{gk} + c_0 \quad (36)$$

The settings of the coefficient of each generator are shown in Table 5:

In order to conduct CEF analysis, this paper sets the CEI vector of each generator set as shown below:

$$E_G = [0.52, 0.15, 0.38, 0.52, 0.16, 0.28]^T \quad (37)$$

Tracking and allocation of CEFL

When the network loss is ignored, the calculation results of CEI and active flux of each node are shown in Table 6:

TABLE 3 The initial grid parameters of the IEEE-30 system.

Node	Generation		Load		Node	Generation		Load	
	P (MW)	Q (MVar)	P (MW)	Q (MVar)		P (MW)	Q (MVar)	P (MW)	Q (MVar)
1	25.97	1.00	-	-	16	-	-	3.50	1.80
2	60.97	32.00	21.70	12.70	17	-	-	9.00	5.80
3	-	-	2.40	1.20	18	-	-	3.20	0.90
4	-	-	7.60	1.60	19	-	-	9.50	3.40
5	-	-	-	-	20	-	-	2.20	0.70
6	-	-	-	-	21	-	-	17.50	11.20
7	-	-	22.80	10.90	22	21.59	39.57	-	-
8	-	-	30.00	30.00	23	19.20	7.95	3.20	1.60
9	-	-	-	-	24	-	-	8.70	6.70
10	-	-	5.80	2.00	25	-	-	-	-
11	-	-	-	-	26	-	-	3.50	2.30
12	-	-	11.20	7.50	27	26.91	10.54	-	-
13	37.00	11.35	-	-	28	-	-	-	-
14	-	-	6.20	1.60	29	-	-	2.40	0.90
15	-	-	8.20	2.50	30	-	-	10.60	1.90

In this paper, the allocation ratio β is set to 0.5. The comparison of active power output and active load data of the generator before and after the allocation is as the Table 7 shows:

It can be seen that, after allocation, the network loss caused by branch impedance is divided proportionally between the generation side and the load side. After tracing the CEFL, the results are shown in Table 8.

Training process of DRL-Based OCEF solver

The initialization of the power system simulation environment includes two parts: load and generator random initialization and PF initialization. By sampling in the uniform distribution, the active and reactive loads are randomly generated between $[0.6, 1.4]p.u.$. In the IEEE-30 system, node 1, where generator one resides, is the balance node, and nodes where the other five generators reside are PV nodes. The generated load is randomly distributed to all six generators. After the generator output's initialization, the generator's voltage is randomly generated between $[V_{gmin}, V_{gmax}]$. The PF solver in Pypower is used to calculate the AC PF under the current network state, and the initial state s_{g0} of the generator and the initial state s_{b0} of the node are obtained, completing simulation environment state initialization.

The hyperparameter settings involved in Algorithm 1 are shown in Table 9:

Table 10 shows the setting methods and meanings of hyperparameters involved in PPO algorithm.

After the replay buffer stores enough data, the *mini_batch_size* group of samples are randomly selected from the replay buffer to calculate the gradient of the policy network and the value network and update the network. The above sampling and update process will be performed k_{epoch} times when each replay buffer is full.

For the hyperparameters in the training process of policy network and value network, this paper sets them as follows: 1) set the initial value of the learning rate as 3×10^{-4} and adopt the learning rate decay method, which makes the learning rate linearly decreases to 0 with the number of training steps; 2) in gradient backpropagation, gradient truncation is adopted to limit the parameters' update range, and the truncation range is set as $[-0.5, 0.5]$. The above two hyperparameter settings will speed up network training and make the training process more stable.

In addition, this paper also takes the following measures to improve the training process: 1) standardize the advantage function; 2) standardize the input state variables into the network, and save the mean and variance of the state variables, so that the agent can standardize the input variables when it is called as the OCEF solver; 3) smooth the output of reward by using the reward scaling method proposed in (Engstrom et al., 2020); 4) refer to the Open AI Baseline (Baselines, 2022) example and set the parameter eps in the Adam optimizer to 1×10^{-5} (default value is 1×10^{-8}).

TABLE 4 The power transmitted on each branch.

Branch	From node	To node	From node injection		To node injection		Loss	
			P (MW)	Q (MVar)	P (MW)	Q (MVar)	P (MW)	Q (MVar)
1	1	2	10.89	5.09	10.86	2.17	0.026	0.08
2	1	3	15.08	4.09	14.96	5.57	0.127	0.48
3	2	4	16.07	5.21	15.89	6.66	0.178	0.5
4	3	4	12.56	4.37	12.54	4.3	0.018	0.07
5	2	5	13.79	4.51	13.68	6.03	0.11	0.44
6	2	6	20.28	7.42	19.99	8.5	0.289	0.87
7	4	6	22.5	11.38	22.43	11.12	0.066	0.26
8	5	7	13.68	6.21	13.56	6.88	0.12	0.29
9	6	7	9.27	3.17	9.24	4.02	0.031	0.08
10	6	8	24.82	24.43	24.69	23.92	0.128	0.51
11	6	9	5.79	3.36	5.79	3.46	0	0.1
12	6	10	3.31	1.92	3.31	2	0	0.09
13	9	11	0	0	0	0	0	0
14	9	10	5.79	3.46	5.79	3.51	0	0.05
15	4	12	1.67	2.02	1.67	2.04	0	0.02
16	12	13	37	9.26	37	11.35	0	2.1
17	12	14	5.39	0.88	5.35	0.8	0.037	0.08
18	12	15	9.48	1.06	9.41	1.19	0.066	0.12
19	12	16	9.26	0.1	9.18	0.28	0.08	0.18
20	14	15	0.85	0.8	0.85	0.8	0.003	0
21	16	17	5.68	2.08	5.65	2.15	0.031	0.07
22	15	18	9.16	0.76	9.07	0.57	0.097	0.19
23	18	19	5.87	0.33	5.85	0.38	0.022	0.05
24	19	20	3.65	3.78	3.66	3.8	0.009	0.02
25	10	20	5.92	4.62	5.86	4.5	0.052	0.12
26	10	17	3.37	8.01	3.35	7.95	0.023	0.06
27	10	21	2.23	11.67	2.28	11.77	0.044	0.1
28	10	22	3.75	8.48	3.82	8.62	0.062	0.13
29	21	22	19.78	22.97	19.87	23.16	0.093	0.19
30	15	23	8.81	5.25	8.91	5.47	0.109	0.22
31	22	24	2.1	7.8	2.18	7.68	0.078	0.12
32	23	24	7.09	0.88	7.02	0.75	0.066	0.14
33	24	25	3.86	1.77	3.89	1.71	0.035	0.06
34	25	26	3.55	2.37	3.5	2.3	0.046	0.07
35	25	27	7.44	0.66	7.5	0.78	0.063	0.12
36	28	27	6.11	6.08	6.11	6.4	0	0.31
37	27	29	6.17	1.68	6.08	1.51	0.09	0.17
38	27	30	7.12	1.67	6.95	1.35	0.171	0.32
39	29	30	3.68	0.61	3.65	0.55	0.035	0.07
40	8	28	5.31	6.08	5.34	4.33	0.036	0.12
41	6	28	0.77	2.7	0.77	1.75	0.001	0
Total Loss							2.444	8.99

After configuring the aforementioned parameters, Figure 4 and Figure 5 illustrate the agent training process. Figure 4 depicts the immediate reward curve after each agent-environment

interaction during the training process. Figure 5 depicts the agent's average reward for solving the target problem multiple times during the current training round, once every 512 steps.

TABLE 5 The settings of the coefficient of each generator.

Generator	Connecting node	c_2	c_1	c_0
1	1	0.02	2	0
2	2	0.0175	1.75	0
3	13	0.025	3	0
4	22	0.0625	1	0
5	23	0.025	3	0
6	27	0.00834	3.25	0

The difference between the two curves is that the curve in Figure 4 represents the outcome of the agent's interaction with the environment using random strategies during the training process, whereas the curve in Figure 5 represents the agent's adoption of the action value with the highest probability to interact with the environment, which is a deterministic strategy.

As shown by the curve in Figure 4, during the first one million training steps, the agent made numerous random attempts and then began to find an effective way to obtain greater rewards. The curve can also show this process in Figure 5. With the agent's exploration, within one million to two million steps, the agent can obtain stable good immediate rewards. The fluctuation curve in both figures indicates that the agent will continue to explore. Currently, as a result of the ongoing optimization of the strategy, the curve in Figure 5 is

also gradually increasing. After two million steps, the agent's strategy is effective and stable.

The verification of solution effect

To evaluate the effectiveness of the DRL-based solver proposed in this paper, the generator dispatching outcomes of OCEF and OPF are compared. Simultaneously, NSGA-II (Deb et al., 2002) with a population of 100 is utilized to solve OCEF, compared to the proposed method to validate its performance.

The generator dispatching results under OCEF obtained by the proposed solver are compared to the dispatching results under OPF to determine whether the results under OCEF can effectively balance the two objectives. When the OPF solver of Pypower (based on the interior point method) is utilized for dispatching optimization considering only the generator cost, Table 11 displays the active power output of each generator, the generation cost, and the tracked CEFL.

Table 12 displays the generator dispatching results when the DRL-based OCEF solver is invoked.

It is evident that the DRL-based solver can achieve a balance between the two objectives, which raises the overall cost of power generation by 7.55% but reduces carbon flow loss by 30.95%.

Figure 6 illustrates the performance of the proposed method and NSGA-II in solving the problem with 10,000 random initial

TABLE 6 The calculation results of CEI and active flux.

Node	Active power flux	CEF intensity	Node	Active power flux	CEF intensity
	P (MW)	t/MWh		P (MW)	t/MWh
1	25.97	0.52	16	9.26	0.35
2	71.86	0.21	17	9.05	0.32
3	15.08	0.52	18	9.16	0.35
4	28.62	0.35	19	5.87	0.35
5	13.79	0.21	20	9.57	0.31
6	42.77	0.28	21	2.23	0.28
7	22.95	0.24	22	45.12	0.33
8	24.82	0.28	23	28.01	0.22
9	5.79	0.28	24	9.18	0.24
10	9.10	0.28	25	3.86	0.24
11	0.00	0.00	26	3.55	0.24
12	1.67	0.35	27	40.46	0.43
13	74.00	0.31	28	6.08	0.28
14	5.39	0.35	29	6.17	0.43
15	10.33	0.35	30	10.81	0.43

TABLE 7 The comparison of active power output and active load data.

Node	Generation		Load		Node	Generation		Load	
	Before	After	Before	After		Before	After	Before	After
1	25.97	25.78	-	-	16	-	-	3.50	3.52
2	60.97	60.59	21.70	21.70	17	-	-	9.00	9.08
3	-	-	2.40	2.41	18	-	-	3.20	3.23
4	-	-	7.60	7.64	19	-	-	9.50	9.62
5	-	-	-	-	20	-	-	2.20	2.23
6	-	-	-	-	21	-	-	17.50	17.58
7	-	-	22.80	23.00	22	21.59	21.48	-	-
8	-	-	30.00	30.25	23	19.20	19.05	3.20	3.20
9	-	-	-	-	24	-	-	8.70	8.75
10	-	-	5.80	5.85	25	-	-	-	-
11	-	-	-	-	26	-	-	3.50	3.54
12	-	-	11.20	11.20	27	26.91	26.65	-	-
13	37.00	36.86	-	-	28	-	-	-	-
14	-	-	6.20	6.22	29	-	-	2.40	2.42
15	-	-	8.20	8.24	30	-	-	10.60	10.73
Difference									
Generation		1.222			Load		1.222		

TABLE 8 The comparison of active power output and active load data.

Generator	Generation	Loss tracing	CEFL
	MW	MW	t/h
1	25.97	0.363	0.189
2	60.97	0.738	0.111
3	37.00	0.321	0.122
4	21.59	0.237	0.123
5	19.20	0.265	0.042
6	26.91	0.519	0.145
Total CEFL			0.732

TABLE 9 The hyperparameter settings involved in Algorithm 1.

Hyper-parameter	Value
<i>max_train_steps</i>	3×10^6
<i>max_episode_steps</i>	128
<i>batch_size</i>	512

states. The graph on the left compares the amount of time required to solve a problem when both approaches yield the same result. The figure on the right compares the benefits of the

TABLE 10 Settings of the hyperparameters of the PPO algorithm.

Hyper-parameter	Meaning	Value
γ	The discount factor	0.96
λ	Generalized dominance estimation calculates the coefficient	0.95
ϵ	Truncation range coefficient	0.15
α	Regularization coefficients of policy entropy	0.01
k_{epoch}	Number of network updates	8
<i>mini_batch_size</i>	Batch size of the data sampled in the replay buffer	32

two methods for simultaneously solving 10,000 identical problems. In terms of score and solution time, it can be seen that the method proposed in this paper is superior to NSGA-II. The DRL-based OCEF solver has a relatively stable effect on problems with varying initial conditions.

Figure 7 compares the solution processes of the DRL-based solver and NSGA-II when applied to the same problem. DRL solver does not need an iterative solving process, but adopts the optimal strategy to make decisions and achieves a good solution in several steps. In contrast, NSGA-II requires constant iteration, resulting in a higher computational cost and a slower solution speed.

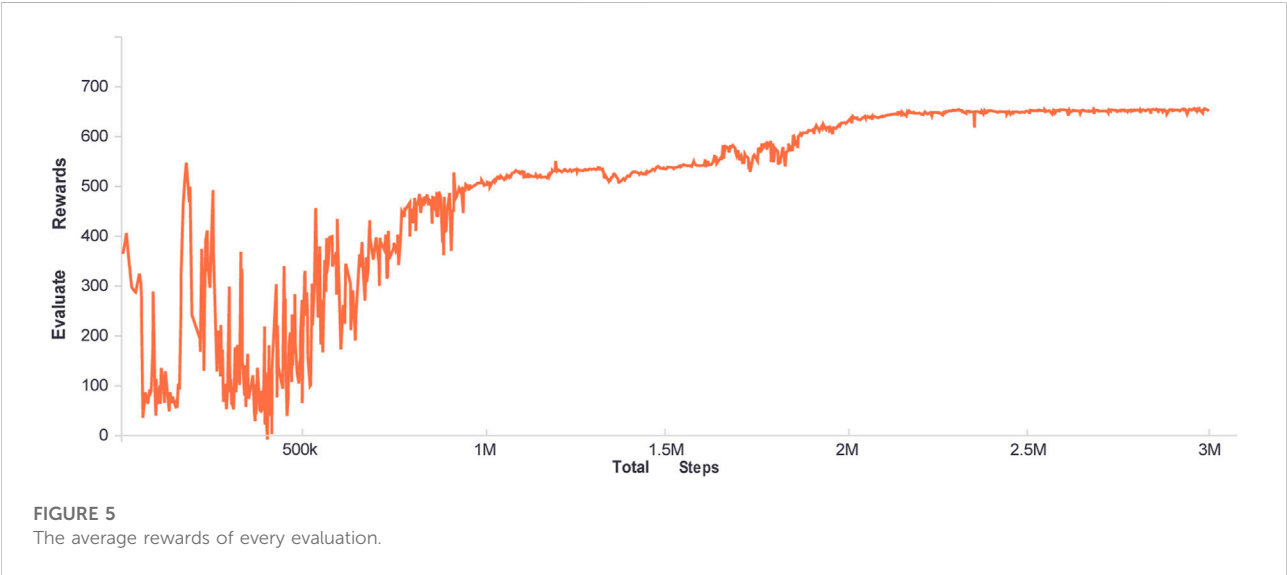
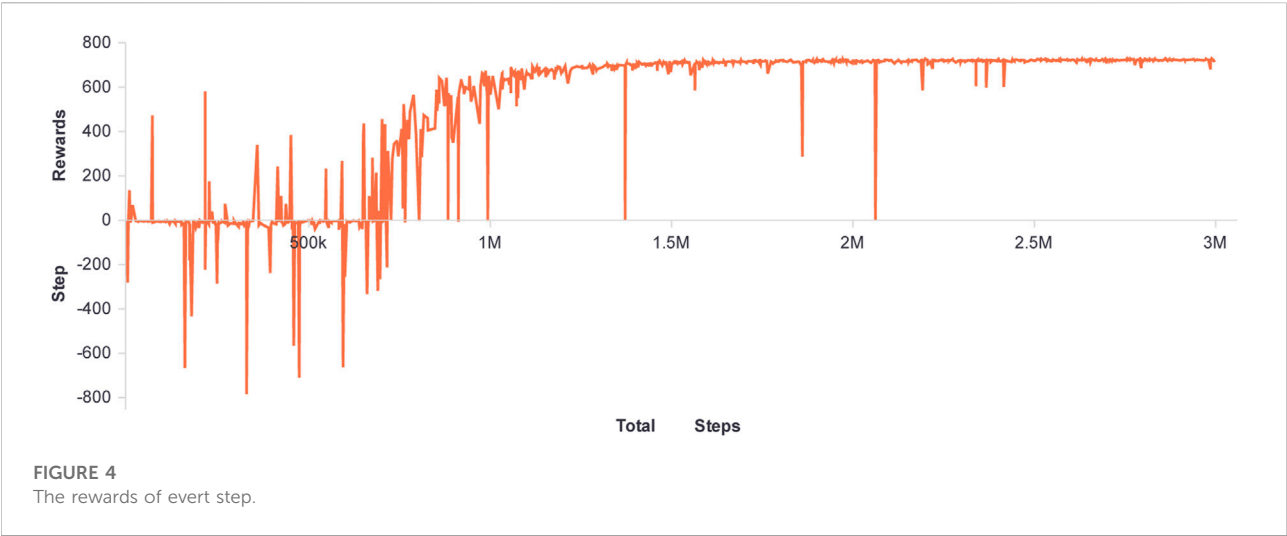


TABLE 11 The dispatching results OF OPF.

Generator	Generation	Cost	Loss
	P (MW)	\$/h	MW
1	41.54	117.59	0.327
2	55.40	150.66	0.103
3	16.20	55.16	0.051
4	22.74	55.06	0.140
5	16.27	55.43	0.035
6	39.91	142.99	0.256
Total	576.89	CEFL (t/MWh)	0.911
Reward	512.11		

TABLE 12 The dispatching results of DRL-based OCEF.

Generator	Generation	Cost	Loss
	P (MW)	\$/h	MW
1	2.73	5.61	0.021
2	59.65	166.65	0.448
3	31.70	120.22	0.220
4	27.63	75.34	0.304
5	24.03	86.53	0.425
6	45.74	166.10	0.863
Total	620.45	CEFL (t/MWh)	0.629
Reward	725.52		

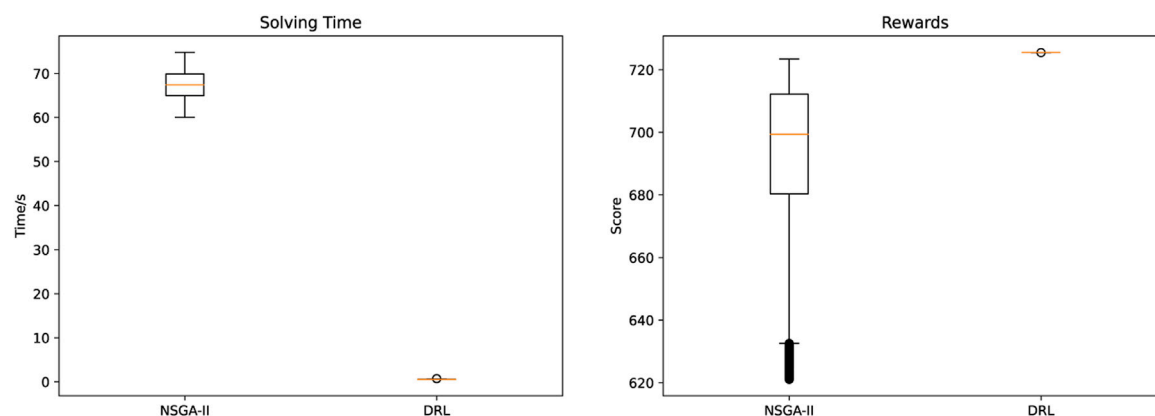


FIGURE 6
The performance comparison.

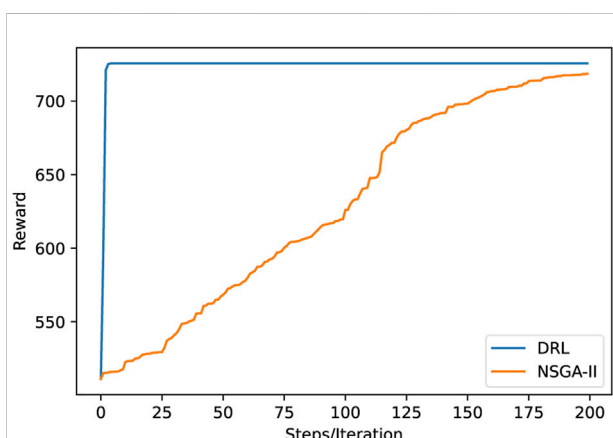


FIGURE 7
The comparison of solution processes.

Conclusion

In this paper, a DRL-based solver for multi-objective OCEF is presented and validated using a case study on the IEEE-30 system. In the case study, the DRL-based solver's solution results are compared to those of NSGA-II. Experimental results indicate that the solution time of the proposed DRL-based OCEF solver is one-hundredth that of NSGA-II, and the solver's performance is enhanced by at least 10 percent. In addition, the DRL-based solver is more stable and can satisfy real-time power dispatching needs.

Following is a summary of future research ideas:

- 1) More intricate dispatching scenarios for power systems can be considered. For instance, constraints such as the N-1 safety constraint and the generator climbing constraint can be

considered, thereby enhancing the practical applicability of the DRL-based solver.

- 2) The actual state parameters of the power system can be used as training data for the model. As demonstrated in the case study, training the agent requires a large amount of data, and each round of interaction requires a time cross-section of system state parameters. In practice, collecting such a vast amount of data is difficult. Consequently, data generation techniques such as the generative adversarial network can be used to provide the necessary training data for DRL agents.
- 3) Consider utilizing the multiagent method to solve the OCEF problem in the larger system. Even though the performance of the DRL-based solution is superior to that of the conventional solution, the larger system still entails a larger action space and state space. This increases the difficulty of calculating the immediate reward value of environmental feedback in a simulated power system and increases network training requirements. When the original large system is partitioned, a single agent is responsible for the dispatching solution of each partition, and multiple agents are combined to reduce training difficulty.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

PQ and QH contributed to the conception and design of the study. PQ and JY performed the analysis. PQ wrote the first draft of the manuscript. PQ, JY, QH, PS, and PK wrote sections of the

manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

Funding

This work was supported by the Science and Technology Project of State Grid Corporation of China under grant to 5419-202040493A-0-0-00.

Conflict of interest

PS and PK were employed by the company State Grid Xinjiang Electric Power Co Ltd.

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 24 July 2022
ACCEPTED 23 August 2022
PUBLISHED 29 September 2022

CITATION
Hu Q, Zhou Y, Ding H, Qin P and Long Y
(2022), Optimal scheduling of multi-
microgrids with power to hydrogen
considering federated
demand response.
Front. Energy Res. 10:1002045.
doi: 10.3389/fenrg.2022.1002045

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Optimal scheduling of multi-microgrids with power to hydrogen considering federated demand response

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Hydrogen is regarded as a promising fuel in the transition to clean energy. Nevertheless, as the demand for hydrogen increases, some microgrids equipped with P2H (MGH) will encounter the issue of primary energy deficiency. Meanwhile, some microgrids (MGs) face the difficulty of being unable to consume surplus energy locally. Hence, we interconnect MGs with different energy characteristics and then establish a collaborative scheduling model of multi-microgrids (MMGs). In this model, a federated demand response (FDR) program considering predictive mean voting is designed to coordinate controllable loads of electricity, heat, and hydrogen in different MGs. With the coordination of FDR, the users' satisfaction and comfort in each MG are kept within an acceptable range. To further adapt to an actual working condition of the microturbine (MT) in MGH, a power interaction method is proposed to maintain the operating power of the MT at the optimum load level and shave peak and shorten the operating periods of MT. In the solution process, the sequence operation theory is utilized to deal with the probability density of renewable energy. A series of case studies on a test system of MMG demonstrate the effectiveness of the proposed method.

KEYWORDS

multi-microgrids, power to hydrogen, demand response, microgrid interaction, energy management

1 Introduction

From the last century to the present, fossil fuels as the world's principal energy have facilitated rapid technological advancement (Arutyunov and Lisichkin, 2017). However, the burning of fossil fuels will result in tremendous pollution emissions that will precipitate a global climate disaster (Kovač et al., 2021; Pan et al., 2021). Under this circumstance, countries around the world are actively exploring environmentally benign energy options (Gielen et al., 2019; Hafner and Tagliapietra, 2020; Zhou et al., 2021). Recently, hydrogen has come into the spotlight again due to its benefits, including the competitive heating value of hydrogen, 142 kJ/g, which is second only to nuclear fuel (Wu

et al., 2019), eradication of environmental harm, and diversified manufacturing approaches (Ishaq and Dincer, 2021). Among all the production approaches, power to hydrogen (P2H) has the advantages of high product purity and fewer by-products of pollutant emissions (Hu et al., 2020). In addition, because of the advantage of integrating various energy technologies and meeting multiple energy demands simultaneously, microgrids (MGs) will be a critical infrastructure for connecting P2H and serving hydrogen demand (so-called MGH) (Pan et al., 2020).

To promote MGH, most researchers have reduced the operating costs of P2H in two ways: 1) diversifying energy sources of P2H and profit channels of product to cut costs and 2) establishing coupling and controlling strategies among P2H and other devices in the microgrid (MG) to reduce energy dissipation. For example, Tostado-Véliz et al. (2021) used multiple energy, including microturbine (MT), grid, and renewable energy generations (RGs), to supply P2H. Meanwhile, MG profits from hydrogen sales to 5-min fueling vehicles. Eghbali et al. (2022) adopted the economic operation strategy of coordinating multiple storage systems, such as electricity storage system (ESS), heat storage system (HST), and hydrogen storage system (HGS). However, large-scale HGS access to MGs still faces technical barriers of high-pressure resistance and leakage prevention. Chahartaghi and Sheykhi, (2019) utilized hydrogen as a working gas of combined cooling, heating, and power generation driven by the Stirling engine (CCHPSE). By controlling the operating parameters of CCHPSE and P2H, pollutant emission reduction and primary energy saving of MG were achieved. Han et al. (2019), Kumar et al. (2020), and Zhang and Wei (2020) proposed a series of control strategies to improve the energy utilization rate and reduce the switching loss of devices in the hydrogen production-storage-distribution process.

It should be pointed out that the aforementioned studies underlie the hypothesis of multiple types of equipment accessing to MGHs. Nevertheless, the economic operation of single-function MGHs, for e.g., hydrogen refueling stations (HFSs), which are only equipped with P2H and a few units for a reserve, is still intractable. For this type of MGH, exploiting more inexpensive primary energy to supply P2H is the most direct and effective means to improve operating economics. Unfortunately, geography and infrastructure impose significant limitations on this approach (Fu et al., 2019) (Ma et al., 2019). In brief, the restrictions of the economic operation of MGH in this situation can be summarized as follows: 1) the distribution of different types of energy is restricted by geography. 2) The demand for hydrogen is not evenly distributed geographically, for example, when fossil fuels can be cheaply obtained and renewable energy is scarce in local, hydrogen will not be the first choice due to more pollutant emissions from the combustion of primary energy of energy-consuming P2H. 3) The infrastructure necessary to transport fossil fuels across regions is inadequate. For example, the transmission of natural gas within Gansu Province of China is tricky due to the much higher

construction cost of the natural gas network than the power grid, which has been well built (Yunna and Ruhang, 2013), ambiguous property rights definition, and lack of unified gas storage standard. 4) It is difficult to transmit hydrogen across regions. The common transmission method, i.e., blending hydrogen into the gas pipeline, greatly degrades durability and integrity of the pipeline on account of hydrogen embrittlement (Pluvinage et al., 2019).

Fortunately, benefiting from the electric power industry with the extensive network coverage in some countries (Yang et al., 2021), the difficulties in the economic operation of MGH can be solved through clustering MGs with different characteristics into multi-microgrids (MMGs). In this context, Karimi and Jadid, (2020) modeled the uncertainty of RGs as a stochastic optimization and proved that off-grid MMGs perform better than grid-connected MMGs in reducing energy losses and pollutant emissions. However, without grid support, dramatic undulation of output of fossil fuel units and drastic fluctuations in the power channels (PCs) between MGs may be caused by load variation. As a result, the wear and tear of equipment and the cost of operation and maintenance also increase (Chapaloglou et al., 2019). Arefifar et al. (2017) designed an energy management success index according to the probability of RGs and load to measure operation cost optimization effect in different scenarios before and after the energy management process. Rezaei and Pezhmani, (2022) constructed an MMG coalition of MGHs with different types and capacities of RGs and utilized an electricity demand response program and carbon trading to reduce the operation cost covering the environmental cost. Nevertheless, there are still few studies on the impact of multiple loads integrated into demand response in the scheduling of MMG.

To solve the aforementioned challenges, a scheduling model considering the different energy structures of various MGs (including MGH) and a power interaction strategy adapting to an actual working condition of units in MGH is proposed in this study. The most significant contributions of this study are summarized as follows:

1) A collaborative scheduling model is established to reduce the operational cost of the off-grid MMG and maximize the utilization of renewable energy. Here, the typical three types of microgrids, namely, the energy-consuming integrating P2H with thermoelectric property, the energy-producing, and the hybrid) are depicted to participate in MMG scheduling. Moreover, the renewable energy with uncertainty is processed with the sequence operation theory, and the scheduling potential of multiple loads in various MGs is explored.

2) A federated demand response programming considering predictive mean voting (PMV) is designed to coordinate loads of schedulable electricity, heat, and hydrogen in different MGs. By this means, the multi-type demands are met, while the user satisfaction and comfort in each MG are kept within an acceptable range.

3) A power interaction method suitable for an actual scenario of constant transmission power on the power channels and weak

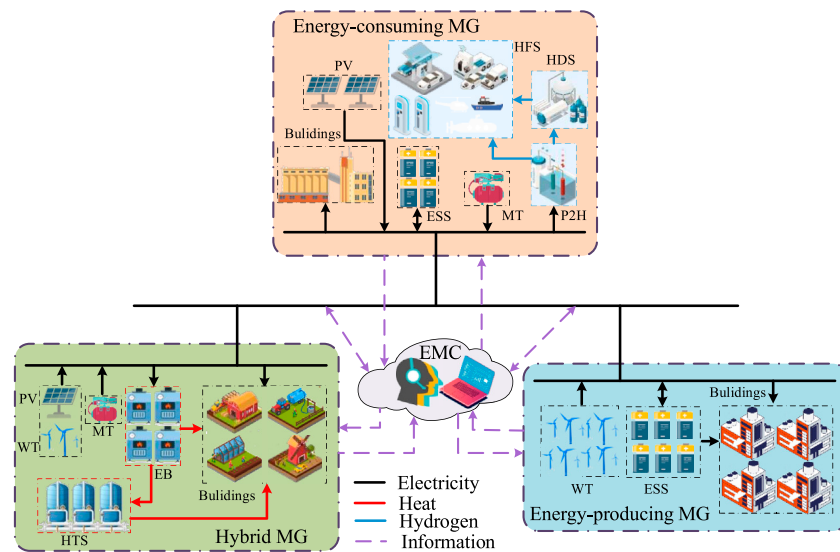


FIGURE 1
Multi-microgrid architecture.

power regulation capability of MT in MGH is proposed. By this method, the operating periods of MT are cut, and the peak is shaved. However, the MT operates at the optimum load level so that continual variation of the output of MT is alleviated and wear and tear of equipment is reduced.

The rest of the article is structured as follows: Section 2 illustrates the architecture of MMG; in Section 3, the collaborative scheduling model of MMG is established; a set of simulations on a test system is carried out in Section 4 to prove the effectiveness of the proposed method; and conclusions are drawn in Section 5.

2 Multi-microgrid architecture

As shown in Figure 1, MMG discussed in this study consists of three types of MGs: the energy-producing, the energy-consuming (ECM), and the hybrid. Among them, the energy-producing denotes the MG only exporting power; the ECM refers to the MG only importing power, and the hybrid is the MG supporting bidirectional power to other MGs. Each of them is equipped with wind turbines (WTs) or photovoltaic panels (PVs). In addition, electricity storage systems (ESSs), heat storage systems (HTSs), hydrogen storage systems (HDSs), electric boiler (EB), and MT are allocated in different MGs according to respective energy structures. The buildings have electricity or heat loads or both. The HFS in ECM sells the hydrogen power from P2H and HDS for profit.

The MGs are connected through power channels (PCs) and operate in off-grid with the regulation of a centralized energy management center (EMC). When the scheduling program is processed, EMC sends commands to each MG and PC and monitors their real-time operating conditions. In this study,

EMC adapts to two management modes: 1) in the liberty scheduling mode, power fluctuation on PC is free from control, and all devices in MMG are flexible enough to accept scheduling; and 2) in the constant power transmission mode, the weak power regulation ability of MG in ECM and constant power transmission with the assistance of high-voltage power transmission (Ambriz-Pérez et al., 2008; Okba et al., 2012) are considered, and EMC should conduct the operation command to MT and ESS of ECM in advance.

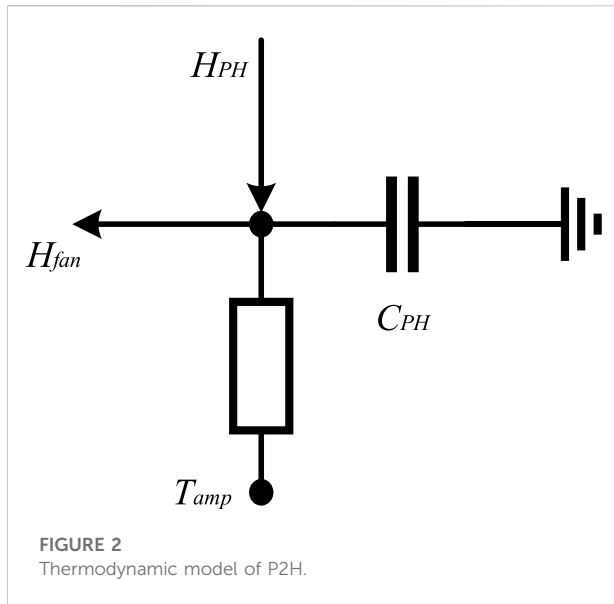
3 Methodology

3.1 Objective function

The objective function of scheduling of MMGs is to minimize the total operation and maintenance costs in the scheduling cycle T as follows:

$$\min C_{total} = \min \left\{ \sum_{t=1}^T \sum_{j=1}^J [C_{fuel,j}(t) + C_{FDR,j}(t) + C_{SPC,j}(t) + C_{env,j}(t)] + \sum_{t=1}^T \sum_{l=1}^{\frac{1}{2}J(J-1)} C_{PC,l}(t) \right\}, \quad (1)$$

where C_{total} is the total operation and maintenance costs of the MMG, $C_{fuel,j}(t)$ is energy transaction cost of the j th MG in the period t , $C_{FDR,j}(t)$ is demand response compensation cost,



$C_{SPC,j}(t)$ is degradation cost of the storage device including ESSs, HTSs, and HDSs, $C_{env,j}(t)$ is environmental cost, and $C_{PC,l}(t)$ is power interaction cost.

$$C_{fuel,j}(t) = \{\kappa_j S_j(t) + U_{MT,j}(t) [\sigma_j + \omega_j P_{MT,j}(t)] - \omega_{hyd} G_{hyd,j}(t)\} \Delta t, \quad (2)$$

where the operating status and start-stop status of microturbine (MT) in the j th MG are denoted as $U_{MT,j}(t)$ and $S_j(t)$, respectively; κ_j , σ_j , and ω_j represent fuel consumption cost coefficient of start-stop, fixed operating, and operating statuses, respectively; $P_{MT,j}(t)$ is the output of the j th MT; ω_{hyd} is the price of hydrogen; and $Q_{MT,j}(t)$ and $G_{hyd,j}(t)$ represent consumed natural gas and sold hydrogen in the j th MG, respectively.

$$C_{FDR,j}(t) = \lambda_{IE} P_j^{IE}(t) + \lambda_{IH} H_j^{IH}(t) + \lambda_{IG} G_j^{IG}(t) + \lambda_{SE} \max\{-P_j^{SE}(t), 0\} + \lambda_{SH} \max\{-H_j^{SH}(t), 0\} + \lambda_{SG} \max\{-G_j^{SG}(t), 0\} \quad (3)$$

where the compensation costs of interrupted electricity load $PIE_j(t)$, interrupted heat load $HIH_j(t)$, and interrupted hydrogen load $GIG_j(t)$ are expressed as λ_{IE} , λ_{IH} , and λ_{IG} , respectively; and λ_{SE} , λ_{SH} , and λ_{SG} are the compensation costs of shifted electricity load $PSE_j(t)$, shifted heat load $HSJ_j(t)$, and shifted hydrogen load $GSG_j(t)$. Notably, only loads interrupted or shifted from the period t are compensated:

$$C_{SPC,j}(t) = \omega_{ESS,j} [U_{dis,j}^{ESS}(t) + U_{cha,j}^{ESS}(t)] \Delta t + \omega_{HTS,j} [U_{dis,j}^{HTS}(t) + U_{cha,j}^{HTS}(t)] \Delta t + \omega_{HDS,j} [U_{dis,j}^{HDS}(t) + U_{cha,j}^{HDS}(t)] \Delta t + \eta_{ESS,j} [P_{dis,j}^{ESS}(t) + P_{cha,j}^{ESS}(t)] \Delta t + \eta_{HTS,j} [H_{dis,j}^{HTS}(t) + H_{cha,j}^{HTS}(t)] \Delta t + \eta_{HDS,j} [G_{dis,j}^{HDS}(t) + G_{cha,j}^{HDS}(t)] \Delta t, \quad (4)$$

where the degradation costs of storage devices include switching degradation costs and discharge/charge degradation costs. $U_{dis,j}^{ESS}(t)$, $U_{cha,j}^{ESS}(t)$, $U_{dis,j}^{HTS}(t)$, $U_{cha,j}^{HTS}(t)$, $U_{dis,j}^{HDS}(t)$, and $U_{cha,j}^{HDS}(t)$ are all binary and indicate the discharge and charge states of ESS, HTS, and HDS in the j th MG, respectively. The unit switching degradation costs of ESS, HTS, and HDS are $\omega_{ESS,j}$, $\omega_{HTS,j}$, and $\omega_{HDS,j}$, respectively. $P_{dis,j}^{ESS}(t)$, $P_{cha,j}^{ESS}(t)$, $H_{dis,j}^{HTS}(t)$, $H_{cha,j}^{HTS}(t)$, $G_{dis,j}^{HDS}(t)$, and $G_{cha,j}^{HDS}(t)$ express the discharge and charge energy of ESS, HTS, and HDS in the j th MG, respectively. $\eta_{ESS,j}$, $\eta_{HTS,j}$, and $\eta_{HDS,j}$ are unit discharge/charge degradation costs.

$$C_{env,j}(t) = \omega_{pen,j} \rho_j \eta_{MT} H_{CV} Q_{MT,j} \Delta t, \quad (5)$$

$$C_{PC,l}(t) = \lambda_{exe,l} |P_l(t)| \Delta t, \quad (6)$$

where ρ_j and $\omega_{pen,j}$ are pollution emission intensity of the MT and penalty cost of the pollutant and $\lambda_{exe,l}$ and $P_l(t)$ represent the unit power interaction cost and interacted power on the l th PC, respectively.

3.2 Constraints

a) Power to hydrogen

The P2H utilizes electricity for water splitting and produces hydrogen power and heat power, which can be expressed as follows (Pan et al., 2020):

$$\begin{cases} G_{PH}(t) = a_1 P_{PH}(t) + b_1 T_{PH}(t), \\ H_{PH}(t) = a_2 P_{PH}(t) + b_2 T_{PH}(t), \end{cases} \quad (7)$$

where $T_{PH}(t)$ is the operating temperature of P2H; $P_{PH}(t)$, $G_{PH}(t)$, and $H_{PH}(t)$ denote input electricity, produced hydrogen power, and produced heat power, respectively; and a_1 , b_1 , a_2 , and b_2 are parameters approximated by linearizing the operation region of P2H.

To avoid heat power build-up that would cause the temperature to exceed critically and destroy the devices, the fan assists in cooling. Meanwhile, similar to thermodynamic properties of buildings (Lu et al., 2020), this study considers the thermodynamic model of P2H, as shown in Figure 2.

$$T_{PH}(t+1) = T_{PH}(t) + \frac{\Delta t}{C_{PH}} [H_{PH}(t) - H_{fan}(t) - H_{loss}(t)], \quad (8)$$

$$H_{loss}(t) = \frac{1}{R_{PH}} [T_{PH}(t) - T_{amp}(t)], \quad (9)$$

$$T_{PH,min} \leq T_{PH}(t) \leq T_{PH,max}, \quad (10)$$

where the thermal resistance and capacity of P2H are equal to R_{PH} and T_{PH} ; $T_{amp}(t)$ is the environment temperature; $H_{fan}(t)$ is the heat extracted by the cooling fan; and $H_{loss}(t)$ is heating loss. $T_{PH,min}$ and $T_{PH,max}$ are required for upper and lower operating temperatures.

b) Federated demand response

Federated demand response (FDR) integrates schedulable loads in all MGs so that demand response characteristics are present in the interior of each MG and the exterior of MMG. The schedulable electricity load can be expressed as

$$\begin{aligned} P_j(t) &= P_{0j}(t) + P_j^{SE}(t) - P_j^{IE}(t), \\ -P_{j,max}^{SE} &\leq P_j^{SE}(t) \leq P_{j,max}^{SE}, \\ \sum_{t=1}^T P_j^{SE}(t) &= 0, \\ 0 &\leq P_j^{IE}(t) \leq P_{j,max}^{IE}, \end{aligned} \quad (11)$$

where $P_{0j}(t)$ and $P_j(t)$ are electricity load before and after scheduling in the j th MG, P_j^{SE}, max denotes the upper bound of the shifted electricity load, and P_j^{IE}, max represents the upper bound of interrupted electricity.

The schedulable hydrogen load is similar to the electricity load as follows:

$$\begin{aligned} G_j(t) &= G_{0j}(t) + G_j^{SG}(t) - G_j^{IG}(t), \\ G_{j,min}^{SG} &\leq G_j^{SG}(t) \leq G_{j,max}^{SG}, \\ \sum_{t=1}^T G_j^{SG}(t) &= 0, \\ 0 &\leq G_j^{IG}(t) \leq G_{j,max}^{IG}. \end{aligned} \quad (12)$$

The heat load is related to indoor and outdoor temperature (Pan et al., 2017; Li et al., 2020). In this study, a transient heat balance equation is used to depict a connection between the heat load and temperature, which can be expressed as

$$H_{0j}(t) = \frac{T_{in,j}(t) - T_{amp,j}(t) + \frac{K_j F_j [T_{in,j}(t) - T_{amp,j}(t)]}{c_{air} \rho_{air} V_j} \Delta t}{\frac{1}{K_j F_j} + \frac{1}{c_{air} \rho_{air} V_j} \Delta t}, \quad (13)$$

where $T_{in,j}(t)$ and $T_{amp,j}(t)$ are indoor and outdoor temperatures ($^{\circ}\text{C}$), respectively; K_j , F_j , and V_j denote integrated heat transfer coefficient ($\text{W}\cdot\text{m}^{-2}\cdot^{\circ}\text{C}^{-1}$), surface area (m^2), and volume (m^3) for buildings, respectively; and c_{air} and ρ_{air} are specific heat capacity ($\text{kJ}\cdot\text{kg}^{-1}\cdot^{\circ}\text{C}^{-1}$) and density ($\text{kg}\cdot\text{m}^{-3}$) for air, respectively. Meanwhile, the PMV index (Mao et al., 2019) is introduced to describe the acceptable heat comfort range for users:

$$PMV = 2.43 - \frac{3.76(T_s - T_{in})}{M(I_{cr} + 0.1)}, \quad (14)$$

where M is the human energy metabolism rate, I_{cr} is the heat resistance of clothing, and T_s is the average skin temperature. The variation range of PMV can be represented as

$$\begin{cases} -0.9 \leq PMV \leq 0.9, & \text{else,} \\ -0.5 \leq PMV \leq 0.5, & t \in [8:00 - 19:00]. \end{cases} \quad (15)$$

The interrupted and shifted heat load is similar to Eq. 11 given as

$$\begin{aligned} -H_{j,max}^{SH} &\leq H_j^{SH}(t) \leq H_{j,max}^{SH}, \\ \sum_{t=1}^T H_j^{SH}(t) &= 0, \\ 0 &\leq H_j^{IH}(t) \leq H_{j,max}^{IH}. \end{aligned} \quad (16)$$

To consider the energy satisfaction of electricity, heat, and hydrogen in all MGs concurrently, a federated demand response satisfaction index (CDI) is designed, which is the average of the demand response satisfaction index of electricity (ESI), heat (HSI), and hydrogen (GSI), as follows:

$$CDI(t) = \frac{\sum_{j=1}^J \frac{P_{0j}(t) - |P_j(t) - P_{0j}(t)|}{P_{0j}(t)} + \sum_{j=1}^J \frac{H_{0j}(t) - |H_j(t) - H_{0j}(t)|}{H_{0j}(t)} + \sum_{j=1}^J \frac{G_{0j}(t) - |G_j(t) - G_{0j}(t)|}{G_{0j}(t)}}{3J}. \quad (17)$$

c) Microturbine and electric boiler

The output of MT obeys the constraints as follows:

$$\begin{aligned} P_{MT,j}(t) &= \omega_{gas} \eta_{MT} H_{CV} Q_{MT,j}(t), \\ U_{MT,j}(t) P_{MT,j,min} &\leq P_{MT,j}(t) \leq U_{MT,j}(t) P_{MT,j,max}, \\ S_j(t) RA_{j,min} &\leq P_{MT,j}(t) - P_{MT,j}(t-1) \leq S_j(t) RA_{j,max}, \end{aligned} \quad (18)$$

where ω_{gas} , η_{MT} , and H_{CV} denote the cost of per unit natural gas, efficiency coefficient of MT, and calorific value of natural gas and $RA_{j,min}$ and $RA_{j,max}$ are the lower and upper bound of ramping power of the MT in the j th MG, respectively.

The operation of electric boiler (EB) obeys the constraints as follows:

$$\begin{aligned} H_{EB,j}(t) &= \eta_{EB} P_{EB,j}(t), \\ H_{EB,j,min} &\leq H_{EB,j}(t) \leq H_{EB,j,max}, \end{aligned} \quad (19)$$

where $P_{EB,j}(t)$, η_{EB} , and $H_{EB,j}(t)$ denote the electric power consumed by EB, electrothermal efficiency of EB, and heat power output by EB, respectively.

d) Storage device

ESS, HTS, and HDS share similar charge/discharge characteristics. Taking ESS as an example, it satisfies the constraints of charge/discharge power and capacity as follows:

$$\begin{aligned} P_{dis,j,min}^{ESS} &\leq P_{dis,j}^{ESS}(t) \leq P_{dis,j,max}^{ESS}, \\ P_{cha,j,min}^{ESS} &\leq P_{cha,j}^{ESS}(t) \leq P_{cha,j,max}^{ESS}, \\ 0 &\leq U_{dis,j}^{ESS}(t) + U_{cha,j}^{ESS}(t) \leq 1, \\ C_j^{ESS}(t+1) &= (1 - k_{loss}) C_j^{ESS}(t) + [\eta_{cha}^{ESS} P_{cha,j}^{ESS}(t) - P_{dis,j}^{ESS}(t) / \eta_{dis}^{ESS}] \Delta t, \\ \alpha_L S_j^{ESS} &= C_{j,min}^{ESS} \leq C_j^{ESS}(t) \leq C_{j,max}^{ESS} = \alpha_U S_j^{ESS}, \end{aligned} \quad (20)$$

where $C_j^{ESS}(t)$ is the capacity of ESS in the j th MG; k_{loss} , η_{dis}^{ESS} , and η_{cha}^{ESS} are its loss rate, discharging, and charging efficiency, respectively; S_j^{ESS} is rated capacity of ESS in the j th MG; and $[\alpha_L, \alpha_U]$ is the SOC range allowed for charge and discharge.

e) Energy balance

The balance equations of electricity, heat, and hydrogen powers in each MG are expressed as Eqs. (21)–(23). In particular, $L_j^e(t)$ is used to offset the energy imbalance caused by the excessive renewable energy generations' (RGs') output:

$$\sum_{l \rightarrow j} P_l(t) + E(P_j^{DG}(t)) + P_{MT,j}(t) + P_{dis,j}^{ESS}(t) + P_{EB,j}(t) = P_j(t) + P_{PH}(t) + P_{cha,j}^{ESS}(t) + L_j^e(t), \quad (21)$$

$$H_{EB,j}(t) + H_{dis,j}^{HST}(t) = H_{cha,j}^{HST}(t) + H_j(t), \quad (22)$$

$$G_{PH}(t) + G_{dis,j}^{HDS}(t) = G_{cha,j}^{HDS}(t) + G_j(t). \quad (23)$$

3.3 Model transformation

The nonlinear terms and the uncertainty of output of RGs in the proposed scheduling model pose a difficulty for the solution. In this section, linearization and sequence operation methods transform the original model to be a MILP which is solvable for CPLEX.

a) Elimination of maximum operators

To eliminate $\max\{\cdot\}$ in Eq. 3, a set of continuous variables and binary variables are introduced. Taking $\max\{-PSE_j(t), 0\}$ as an example,

$$\begin{cases} P_j^{SE}(t) = -\varepsilon_1(t)P_{\max}(t) + \varepsilon_2(t)*0 + \varepsilon_3(t)P_{\max}(t), \\ \max\{-P_j^{SE}(t), 0\} = \varepsilon_1(t)P_{\max}(t), \\ \varepsilon_1(t) + \varepsilon_2(t) + \varepsilon_3(t) = 1, \\ \theta_1(t) + \theta_2(t) + \theta_3(t) = 1, \\ \varepsilon_1(t) \leq \theta_1(t), \varepsilon_2(t) \leq \theta_1(t) + \theta_2(t), \varepsilon_3(t) \leq \theta_2(t) + \theta_3(t), \end{cases} \quad (24)$$

where $\varepsilon_1, \varepsilon_2$, and ε_3 are continuous variables and θ_1, θ_2 , and θ_3 are binary variables.

b) Elimination of absolute operators

To eliminate $|\cdot|$ in Eqs. 6–17, a set of continuous variables and binary variables is introduced. Taking $|P_j(t) - P_{j0}(t)|$ as an example,

$$\begin{cases} |P_j(t) - P_{j0}(t)| = P_j^+(t) + P_j^-(t), \\ P_j(t) - P_{j0}(t) = P_j^+(t) - P_j^-(t), \\ P_j^+(t) \geq 0, P_j^-(t) \geq 0. \end{cases} \quad (25)$$

c) Probabilistic sequence of RGs

The outputs of WT and PV are intermittent and random, and probability density functions (PDFs) are usually used to describe the uncertainty. WT output and PV output obey the Weibull distribution and Beta distribution, respectively. In the period t ,

the sequence operation (SO) (Kang et al., 2002; Li et al., 2020) is used to discretize their respective PDFs according to the preset discretization step length, and then the probabilistic sequences $a(i_{a,t})$ are obtained. Taking the WT as an example, the length of the WT output sequence is as follows:

$$N_{a,t} = \lceil P_{\max,t}^{WT}/q \rceil, \quad (26)$$

where $\lceil x \rceil$ represents the largest integer less than x , $P_{\max,t}^{WT}$ represents the maximum output of the WT in period t , and q denotes the discretization step length. The WT output sequence can be calculated as

$$a(i_{a,t}) = \begin{cases} \int_0^{q/2} f_o(P^{WT})dP^{WT}, & i_{a,t} = 0, \\ \int_{i_{a,t}q-q/2}^{i_{a,t}q+q/2} f_o(P^{WT})dP^{WT}, & i_{a,t} > 0, i_{a,t} \neq N_{a,t}, \\ \int_{i_{a,t}q-q/2}^{i_{a,t}q} f_o(P^{WT})dP^{WT}, & i_{a,t} = N_{a,t}, \end{cases} \quad (27)$$

$$E(P_t^{WT}) = \sum_{u_{a,t}=0}^{N_{a,t}} u_{a,t} q a(u_{a,t}), \quad (28)$$

where $E(P_t^{WT})$ is the expected output of WT in the period t . The expected output of PV is similar to the aforementioned equation.

3.4 Constant power interaction method

The violent power fluctuation on PCs will bring negative effects such as shortened equipment life, increased operation and maintenance costs, and increased construction costs of the channel and auxiliary devices. In addition, MT equipped in ECM like HFS is rarely equipped with a complete power regulating system, including fuel servo and speed control, so it is tough to accept dramatic changes in output. Under this circumstance, it is a popular method to set a fixed charge/discharge threshold (SFT) for the ESS in ECM according to the net load, thereby alleviating the power regulation pressure of the MT (Wang et al., 2013; Lucas and Chondrogiannis, 2016). However, the threshold is easy to increase the extra operating time of the MT. In order to improve operating efficiency and decrease operating periods of MT in ECM, we propose an MMG interaction method suitable for the scenario of the PC constant power:

The power of the PC connected to the ECM satisfies

$$P_l^{opt}(1 - \alpha_l) \leq P_l(t) \leq P_l^{opt}(1 + \alpha_l); \forall l \rightarrow ECM, \quad \sum_{l \rightarrow ECM} P_l(t) = P_{IEC}^{opt}, \quad (29)$$

where P_l^{opt} is the optimum transmission capacity on the l th PC connected to the ECM, which is allowed to fluctuate within $[1 - \alpha_l, 1 + \alpha_l]$, and the optimum total power transmitted to ECM is kept as P_{IEC}^{opt} .

We define optimum load capacity of MT in ECM as

$$P_{MT}^{ECO} = \mu_{MT} S_{MT}^{EC}, \quad (30)$$

where S_{MT}^{EC} is the installed capacity of MT in ECM and μ_{MT} is the optimum load coefficient. In the PC constant power scenario, MT in ECM is off or operates at an optimum load capacity.

Algorithm 1. Constant power interaction method.

```

1: Initialization: input parameters of MMG, Set  $P_{ECN} = P_{EC} + P_{PH,EC} - E(P_{EC}^{DG})$ 
2: For  $t = 1:T$ 
3: Switch  $((P_{ECN}(t), C_{EC}^{ESS}(t)))$ 
{
4: Case A  $(P_{ECN}(t) > P_{IEC}^{opt} + P_{MT}^{ECO}$  and  $C_{EC,min}^{ESS} < C_{EC}^{ESS}(t) < C_{EC,max}^{ESS})$ :
 $P_{dis,EC}^{ESS}(t) = P_{ECN}(t) - P_{IEC}^{opt}$ ;  $S_{EC}(t) = 1$ ; break;
5: Case B  $(P_{IEC}^{opt} + P_{MT}^{ECO} > P_{ECN}(t) > S_{EC}^{ESS} + P_{IEC}^{opt}$  and  $C_{EC,min}^{ESS} < C_{EC}^{ESS}(t)$ 
 $< C_{EC,max}^{ESS})$ :  $P_{cha,EC}^{ESS}(t) = P_{IEC}^{opt} + P_{MT}^{ECO} - P_{ECN}(t)$ ;  $S_{EC}(t) = 1$ ; break;
6: Case C  $(S_{EC}^{ESS} + P_{IEC}^{opt} > P_{ECN}(t) > P_{IEC}^{opt}$  and  $C_{EC,min}^{ESS} < C_{EC}^{ESS}(t)$ 
 $< C_{EC,max}^{ESS})$ :  $P_{dis,EC}^{ESS}(t) = P_{ECN}(t) - P_{IEC}^{opt}$ ;  $S_{EC}(t) = 0$ ; break;
7: Case D  $(P_{IEC}^{opt} > P_{ECN}(t) > P_{IEC}^{opt} - S_{EC}^{ESS})$ :  $P_{dis,EC}^{ESS}(t) = 0$ ;  $P_{cha,EC}^{ESS}(t) = 0$ ;
 $S_{EC}(t) = 0$ ; break;
8: Case E  $(P_{ECN}(t) < P_{IEC}^{opt} - S_{EC}^{ESS}$  and  $C_{EC,min}^{ESS} < C_{EC}^{ESS}(t) < C_{EC,max}^{ESS})$ :
 $P_{dis,EC}^{ESS}(t) = P_{IEC}^{opt} - P_j^{EC}(t)$ ;  $S_{EC}(t) = 0$ ; break;
}
9: end for
10: Obtain  $\{S_{EC}, P_{dis,EC}^{ESS}, P_{cha,EC}^{ESS}\}$ 

```

4 Case study

In this study, an MMG is used as a simulation system to examine the effectiveness of the proposed method, as shown in Figure 3. The MGH is an energy-consuming MG, the MGB is an energy-producing MG, and the MGC is a hybrid MG. All tests are carried out for 24 h, each time with an 1-h increment. The expected output of RGs in the three MGs processed in the method introduced in 3.3, the indoor and outdoor temperature of MGB, and loads in each period are shown in Figure 4. The maximum outputs of the PV in MGH and MGB are 500 and 300 kW, respectively. The maximum outputs of the WT in MGB and MGC are 600 and 500 kW, respectively. The discretization step length is 5 kW.

The parameters of main equipment in MMG are as follows: $P_{dis,max}^{ESS} = 25$ kW, $P_{cha,max}^{ESS} = 25$ kW, $S^{ESS} = 100$ kW, $\eta_{dis}^{ESS} = \eta_{cha}^{ESS} = 0.9$, $P_{MT,max} = 500$ kW, $RA_{j,max} = 200$ kW, $RA_{j,min} = -200$ kW, $G_{dis,max}^{HDS} = 100$ kW, $G_{cha,max}^{HDS} = 100$ kW, $S^{HDS} = 300$ kW, $H_{dis,max}^{HTS} = 60$ kW, $H_{cha,max}^{HTS} = 60$ kW, $S^{HTS} = 120$ kW, $H_{EB} = 300$ kW, and $\eta_{EB} = 0.99$. The upper bound of the time-shifted and the interrupted hydrogen load are 15% and 10% of the total hydrogen load, respectively. The upper bound of the time-shifted and the interrupted heat load in MGB are 15% and 10% of the total heat load, respectively. The upper bound of the time-shifted and the interrupted electricity load in MGC are

15% and 10% of the total electricity load, respectively. In addition, the parameters related to other equipment operating are referred to Li et al. (2019), Pan et al. (2020), and Huang et al. (2022).

4.1 The impact of the connection structure of MMG

To verify the effectiveness of the cluster mode in assisting the operation of MGH, four scenarios are set. Scenario 1: disconnect all PCs of MMG, i.e., MGH, MGB, and MGC operate in isolation. Scenario 2: connect MGB with MGC, and MGH operates in isolation. Scenario 3: based on Scenario 2, connect MGH with MGC. Scenario 4: interconnect MGH, MGB, and MGC.

Table 1 shows the total operation and maintenance costs, environmental cost, and RGs curtailment of MMG in different connection structures of MMG. It can be observed that, in scenario 1, when all PCs of MMG are disconnected, the three MGs can only supply loads through their own energy source, which results in excess RGs in the MGB. The energy of MGH is insufficient, and it is necessary to increase its own MT output to maintain the balance between supply and demand, resulting in a significant increase in pollutant emissions.

Compared with Scenario 1 and Scenario 2, the addition connection of PC of MGB-MGC in Scenario 2 does not significantly improve the economy. The reason is that MGC is a hybrid system and does not need energy supply from MGB. Hence, it has little influence on improving the consumption of RGs in MGB and thus fails to improve the RG curtailment.

After connecting PC of MGB-MGC in Scenario 3, the MGA can be supplied by MGB through PCs of MGB-MGC and MGC-MGA to reduce the output of MT in the MGH and improve the RG consumption in MGB. Compared with scenario 3, total operation and maintenance costs and pollutant emissions of Scenario 4 are further reduced. The reason is that after connecting the PC of MGB-MGH in Scenario 4, the MGB can directly transmit the excess RGs to the MGC through the PC of MGB-MGH to reduce the transmission cost.

To evaluate the impact of PC capacity on the economic operation of MMG, 21 scenarios with different PC capacities are set, which are 0%, 10%, 20%, . . . , 200% of the default value, respectively.

It can be observed from Figure 5A that, with the increase in the transmission capacity of the PCs, the total operation and maintenance costs, environmental cost, and RG curtailment are gradually reduced and kept constant (extra construction costs are not included) after the transmission capacity of the PCs reaching 200 kW. The analysis shows that the appropriate set of transmission capacity of the PCs is conducive to the reduction of MMG operating cost, emissions, and the increase in RG consumption. Figure 5B compares the impact of the transmission capacity of different PCs. It can be seen that the

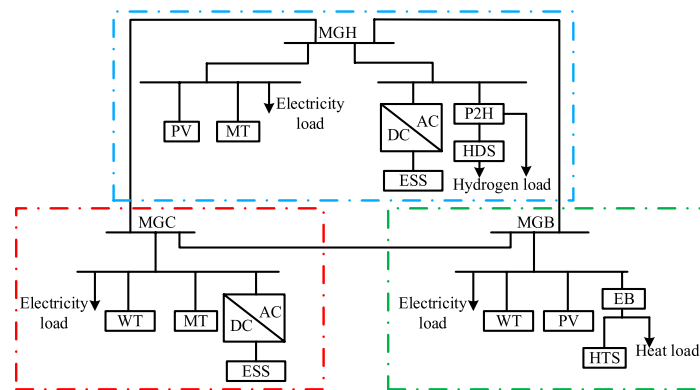


FIGURE 3
MMG test system.

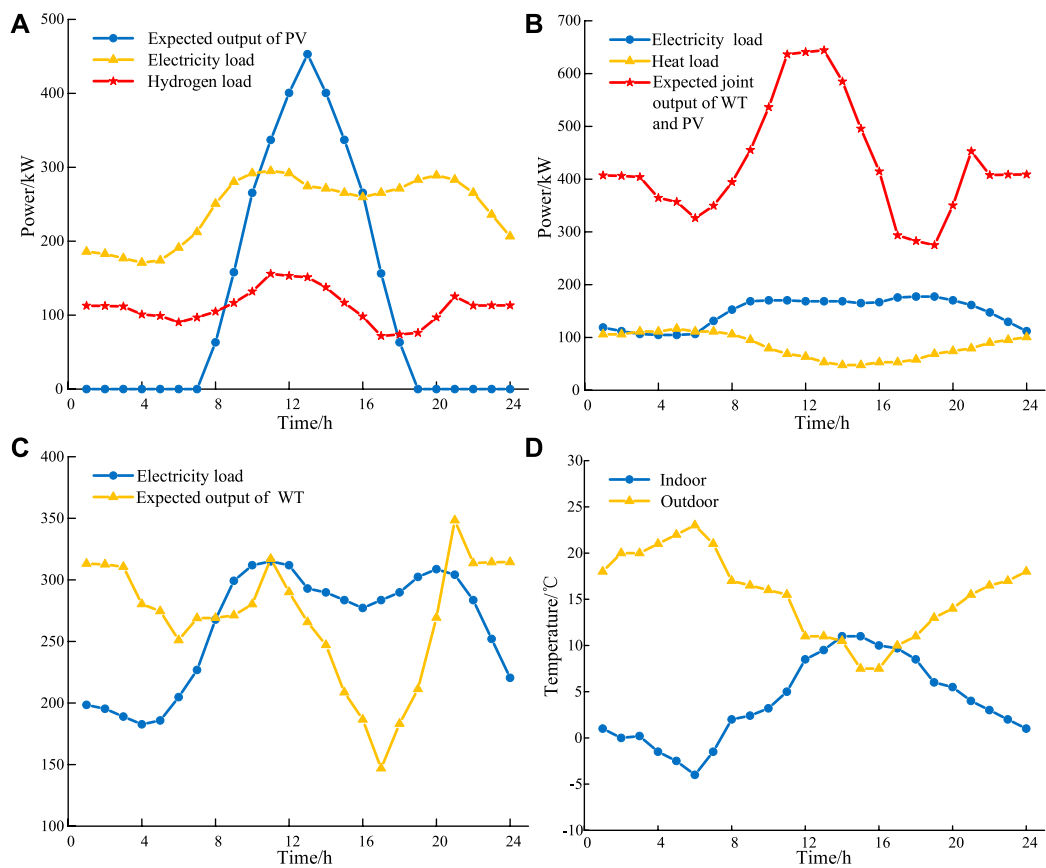
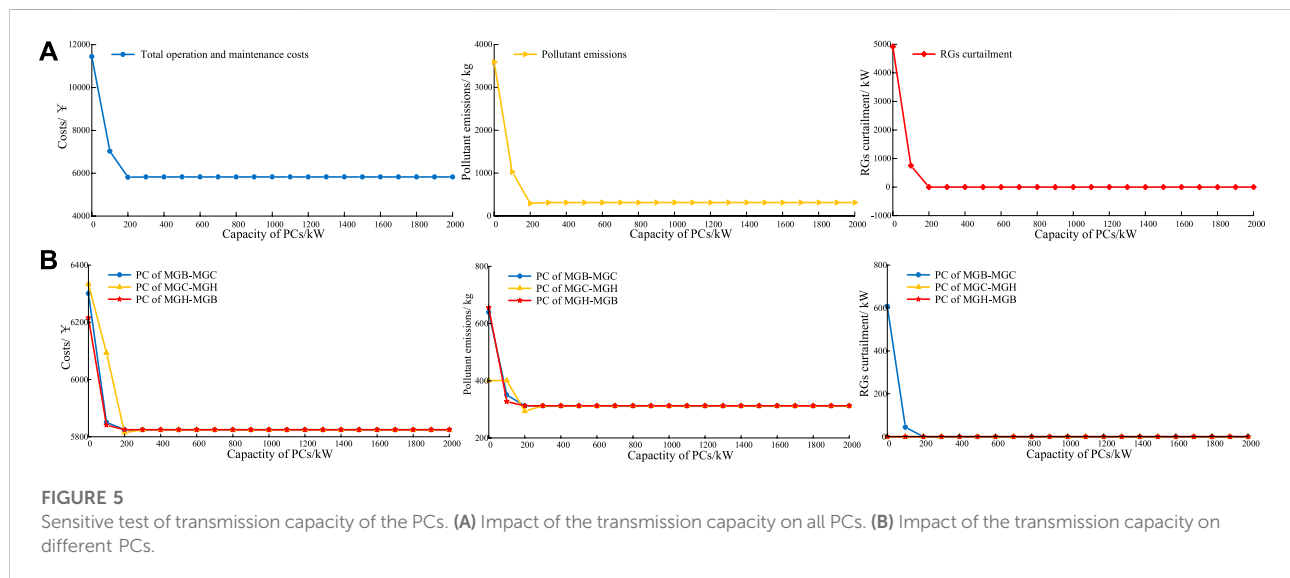


FIGURE 4
Parameters of MGs. (A) Parameters of load and RGs of MGH. (B) Parameters of load and RGs of MGB. (C) Parameters of load and RGs of MGC. (D) Indoor and outdoor temperature of MGB.

TABLE 1 Economic items under different scenarios.

Item	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Total operation and maintenance costs/¥	11,447	11,436	6,333.33	5,824.5
Pollutant emissions/kg	3,590.53	3,590.53	400.97	312.51
RGs curtailment/kW	4,751.66	4,717.31	0.00	0.00



transmission capacity of PC of MGH-MGB has a higher sensitivity to the total operating cost. The reason is that the MGB, the energy-producing, transmits energy to energy-consuming MGH to maintain a balance between the supply and demand. The analysis shows that the transmission capacity of PC of MGH-MGB has a greater impact on the transmission power, which results in a greater impact on the operating cost of MMG.

In terms of pollutant emissions, the transmission capacity of the PC of MGC-MGH is more sensitive. The reason is that pollutant is mainly emitted by MGH, and the expansion of transmission capacity of the PC of MGC-MGH increases the transmission of RGs to the MGH, thereby reducing pollutant emissions.

4.2 The impact of federated demand response

We illustrate the electricity, heat, and hydrogen load scheduling scheme before and after FDR in Figure 6. It indicates that the electricity, heat, and hydrogen load increases around 12:00 after

the FDR. The reason is that the RG output is sufficient during this period, and the loads are shifted to consume RGs. The analysis shows that the loads are redistributed through FDR, and the consumption level of RG and the MMG operation economy are improved.

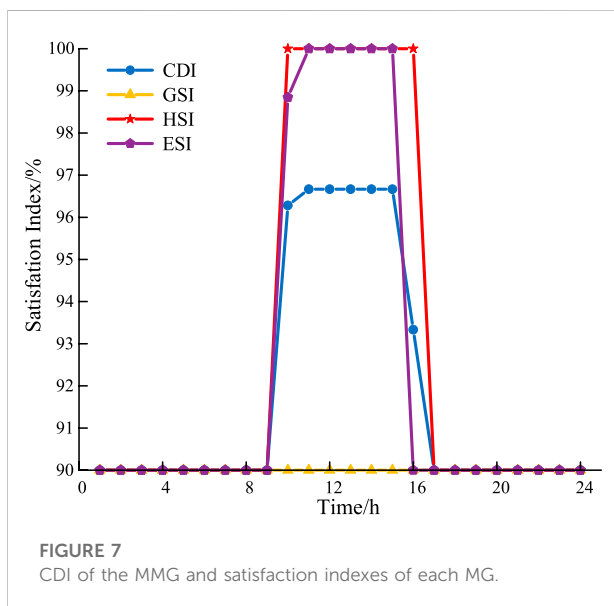
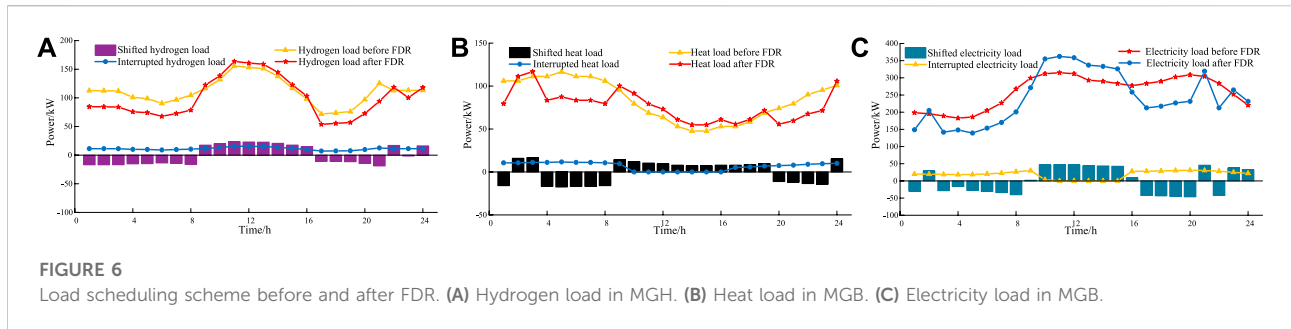
Figure 7 shows the CDI of the MMG and satisfaction indexes of each MG in a scheduling cycle. It can be observed that the satisfaction of MGH is always at the lower bound, which is caused by the lack of its own energy. CDI reflects the overall satisfaction level of the MMG. On the basis of meeting the electricity, heat, and hydrogen demands of MMG, the energy supply pressure can be relieved, and the operation economics of MMG can be improved by reducing the CDI and adjusting the bounds of electricity, heat, and hydrogen demand response.

To analyze the impact of the FDR on the operational costs of MMG, we design four scenarios as follows:

Scenario 1: not considering the demand response.

Scenario 2: considering the demand response of electricity and not considering the demand response of heat and hydrogen.

Scenario 3: considering the demand response of electricity and heat and not considering the demand response of hydrogen.



Scenario 4: considering FDR, that is, demand response of electricity, heat, and hydrogen simultaneously.

Table 2 shows that FDR reduces total operation and maintenance costs by 11.21%, 3.02%, and 1.08% compared with scenarios 1, 2, and 3. Meanwhile, FDR reduces pollutant emissions by 69.74%, 49.36%, and 39.69%, respectively. In addition, only in Scenario 1, RGs are curtailed. The analysis reveals that FDR can effectively save operating and maintenance costs, reduce pollutant emissions, and improve the consumption of RGs.

4.3 The impact of the constant power interaction method

In this section, the simulation results are presented to demonstrate the superiority of the proposed constant power interaction method over the SFT method on operating period

reduction of MG and peak shaving. In the simulation, EC denoting MGH and $P_{ECN}(t)$ is the original net load, which can be calculated using Algorithm 1.

Figure 8 shows the simulation results with the proposed and SFT methods. Here, the ESS in MGH discharges when the net load is above the threshold set by the SFT; otherwise, it charges (Wang et al., 2013). It can be observed from Figure 8A that SOC of ESS with the proposed method has fewer types of the slope than that with the SFC method. It means that the charge/discharge rate of ESS is more stable with the proposed method. The analysis reveals that the proposed method comprehensively considers the net load, load level of MT, and capacity of ESS to improve the charging/discharging efficiency.

Figure 8B and Figure 8C indicate that, in the period of {1:00, 2:00, 3:00, 4:00, 5:00, 6:00, 7:00, 8:00, 18:00, 23:00, 24:00}, $S_{EC}^{ESS} + P_{IEC}^{opt} > P_{ECN}(t) > P_{LEC}^{opt}$ and ESS in MGH start discharging to compensate for the lack of power. However, the capacity reaches its lower bound ($0.1S_{EC}^{ESS}$) in the period of {5:00, 6:00, 7:00, 8:00} so that ESS refuses to discharge. In the period of {9:00, 10:00, 17:00}, $P_{ECN}(t) < P_{IEC}^{opt} - S_{EC}^{ESS}$ and ESS neither charges nor discharges to prevent MG, not operating at optimum efficiency. In the period of {11:00, 12:00, 13:00, 14:00, 15:00, 16:00}, $P_{ECN}(t) < P_{IEC}^{opt} - S_{EC}^{ESS}$ and ESS start charging until the capacity reaches its upper bound ($0.9S_{EC}^{ESS}$) in the period of 15:00. In the period of {19:00, 22:00}, $P_{IEC}^{opt} + P_{MT}^{ECO} > P_{ECN}(t) > S_{EC}^{ESS} + P_{IEC}^{opt}$ and the charge power are the upper bound value and $P_{IEC}^{opt} + P_{MT}^{ECO} - P_{ECN}(t)$, respectively. In the period of {20:00, 21:00}, $P_{ECN}(t) > P_{IEC}^{opt} + P_{MT}^{ECO}$ and $C_{EC,min}^{ESS} < C_{EC}^{ESS}(t) < C_{EC,max}^{ESS}$ and discharge power of ESS are $P_{ECN}(t) - P_{IEC}^{opt}$.

The results of Figure 8C show that the proposed method reduces MT operating periods by 8 h compared with the SFT method. In addition, it can be seen from Figure 8D that the performance of peak shaving when using the proposed method is better than that using the SFT method. It means that the charge of ESS takes full advantage of the power of operating MT, and the discharge of ESS occurs during the peak load periods when the MT is most likely to be started. The analysis reveals the effectiveness of the cases divided in Algorithm 1.

TABLE 2 Comparison of economy under different scenarios of demand response.

Item	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Total operation and maintenance costs/¥	6,559.83	6,005.60	5,888.27	5,824.45
Pollutant emissions/kg	1,032.92	617.13	518.17	312.51
RGs curtailment/kW	239.60	0.00	0.00	0.00

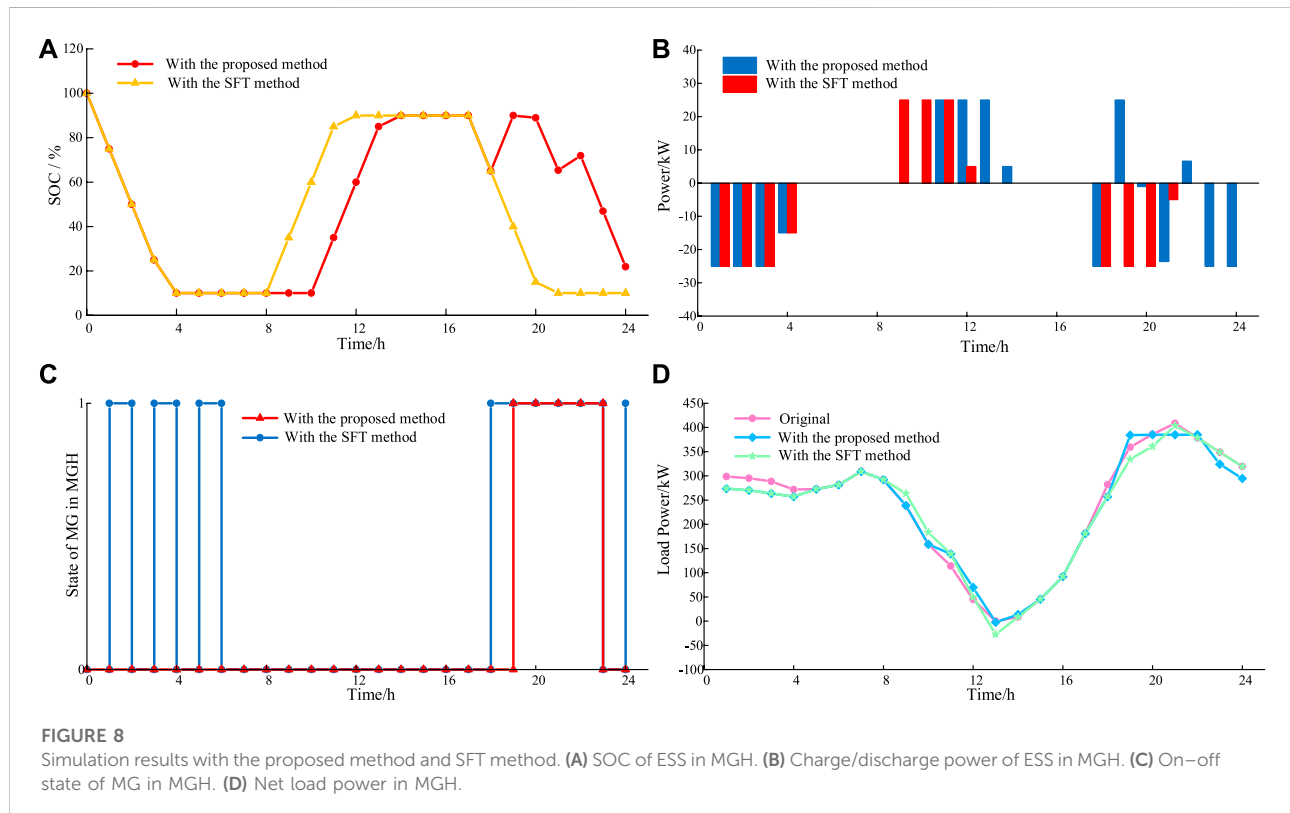


FIGURE 8 Simulation results with the proposed method and SFT method. (A) SOC of ESS in MGH. (B) Charge/discharge power of ESS in MGH. (C) On-off state of MG in MGH. (D) Net load power in MGH.

5 Conclusion

To alleviate the primary energy shortage of some MGHs, we establish a collaborative scheduling model of MMG to coordinate the operation of MGH and other MGs with different characteristics and optimize the cross-regional interaction of energy. In the model, multi-type loads from various MGs participate in scheduling under the coordination of federated demand response. In addition, given the actual scenario of PC constant transmission power and weak power regulation capability of MT in MGH, a power interaction method is designed to improve MT operating efficiency. The simulation results demonstrate the following conclusions:

1) The established collaborative scheduling model of MMG significantly improves the total operating economy and reduces the RGs curtailment of the energy-producing MGB from 4,751.66 kW to 0 kW. Moreover, the total pollutant emissions decrease by 91.3%, and the operating costs decrease by 49.1%. The sensitivity analysis shows that the appropriate configuration of the capacity of PCs is conducive to the economic operation of MMG.

2) The proposed federated demand response program aggregates the loads within MMG as a schedulable grid asset, with CDI reflecting the collective satisfaction of all loads. By keeping the CDI in an acceptable range, the total operation and maintenance costs and pollutant emissions are reduced by 11.21% and 69.74%, respectively, while balancing energy supply and demand.

3) The designed interaction method under the scenario of constant power transmission of PCs efficiently controls the charge/discharge of the ESS and the start/stop of the MT in MGH. Compared with the SFT method, the suggested method enables the MT to operate at an optimum load capacity while reducing the operating time by 61.5% and improving peak shaving performance.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material. Further inquiries can be directed to the corresponding author.

Author contributions

QH and YZ conceived and designed the research. QH and YZ carried out the simulations and analyses. All authors contributed to the discussion on the method and the writing of this manuscript.

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Funding

This work was supported by the Science and Technology Project of State Grid Corporation of China (5108-202218280A-2-0-XG).

Conflict of interest

YL was employed by company State Grid Jiangsu Electric Power Company Limited.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 14 September 2022
ACCEPTED 31 October 2022
PUBLISHED 14 November 2022

CITATION
Gong J, Xiong Y, Wu H, Chen H, Chen J
and Xiao D (2022), Operation strategy
and profitability analysis of independent
energy storage participating in
electricity market: A provincial case
study in China.
Front. Energy Res. 10:1044503.
doi: 10.3389/fenrg.2022.1044503

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Operation strategy and profitability analysis of independent energy storage participating in electricity market: A provincial case study in China

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The new energy storage, referring to new types of electrical energy storage other than pumped storage, has excellent value in the power system and can provide corresponding bids in various types of electricity markets. As the scale of new energy storage continues to grow, China has issued several policies to encourage its application and participation in electricity markets. It is urgent to establish market mechanisms well adapted to energy storage participation and study the operation strategy and profitability of energy storage. Based on the development of the electricity market in a provincial region of China, this paper designs mechanisms for independent energy storage to participate in various markets. Then, its current and future operation strategies by division time or capacity for participation in each type of market are analyzed, and the profitability under various scenarios is calculated. Finally, based on the calculation results, the theoretical analysis basis for developing independent energy storage in the province and the policy formulation of participation in the market is provided.

KEYWORDS

independent energy storage, electricity market, mechanism, provincial case, operation strategy, Profitability

1 Introduction

As early as September 2020, China proposed the goal of “carbon peak” and “carbon neutrality” (Xinhua News Agency, 2020). As a result, a new power system construction plan with renewable energy as the primary power source came into being (Xin et al., 2022). With the large-scale access to renewable energy with greater randomness and volatility to the grid, the balance of power supply and demand, system regulation, control and protection will all undergo significant changes (Xiao et al., 2021; Zhang et al., 2021).

As one of the most valuable flexibility resources, energy storage (ES) is essential in maintaining system power balance (Boicea, 2014).

Currently, ES technology has a wide range of applications on the generation side, the grid side and the user side respectively. Essentially, these applications highlight the flexibility value of ES for the power system. On the generation side, the effect of joint participation of thermal units and ES in frequency regulation is far better than that of separate thermal units; ES can help renewable energy units reduce power fluctuations and power abandonment and increase the revenue in the electricity energy market and reduce deviation assessment fees (Toledo et al., 2010; Zhao et al., 2015; De Siqueira and Peng, 2021). On the grid side, ES can help reduce transmission and distribution losses, ensure the safety of system operation and ease the pressure of peak regulation (Nazemi et al., 2019; Nguyen et al., 2019). On the user side, it can help to consume distributed energy, reduce electricity costs, and participate in demand response (Bradbury et al., 2014; Harsha and Dahleh, 2014; Bitaraf and Rahman, 2017).

According to the statistics of the Energy Storage Committee of China Energy Research Society, by the end of September 2021, the cumulative installed capacity of pumped hydro storage in the world reached 172.5 GW, accounting for 89.3% of all ES. The cumulative installed capacity of electrochemical ES, a representative of new energy storage (NES) that includes other forms of ES in addition to pumped hydro storage, ranked second with 16.3 GW, accounting for 8.5%. Among all kinds of electrochemical ES, lithium batteries have the largest cumulative installed capacity, accounting for 92.8%. While in the past 20 years, the installed capacity of electrochemical batteries has shown explosive growth and has gradually occupied an essential position in developing ES applications (Ralon et al., 2017). In this context, there is an urgent need for a market environment and rational planning that supports the operation and development of NES.

In order to incorporate ES into the market framework, academics have proposed some amendments to the market's trading model. In the energy market model, the state of charge constraints of ES were added to the clearing model to ensure the feasibility of the results in (De Viviero-Serrano et al., 2019). For the capacity value of ES in the capacity market, a simple approach was suggested to be used, where the capacity value is approved based on the historical capacity support performance of ES during peak load periods of the system in (Opathella et al., 2018). For the participation of ES in the ancillary services market, fast frequency response products were designed in (Chen et al., 2021), which are faster than primary frequency regulation response and can effectively address the low inertia of the system, for which ES is an important provider.

In the study of the practical mechanism of ES participation in the electricity market, the United States (Konidena, 2019), Europe (Barbour et al., 2016), Australia (Yu et al., 2019) and other countries have made excellent exploration. In the CAISO model of spot

market, ES can submit price bids, the initial state of charge for a single day, and desired final state of charge. The state of charge constraint of ES is considered by ISO in the clearing model, which ensures the feasibility of the clearing result for ES (CAISO, 2021). In the PJM model of spot market, energy storage must submit price bids and its working state including four types: charging, discharging, continuous, and unavailable. ES will be responsible for managing the state of charge to ensure the feasibility of the charging and discharging plan (PJM, 2019). Considering the fast response characteristics of ES, PJM allows ES without primary energy output to provide auxiliary services such as frequency regulation (Xiao et al., 2020). Regarding analyzing the value of ES capacity, the ISOs have adopted more straightforward rules, requiring ES to meet a continuous discharge time and discounting the discharge power if it cannot. In the United Kingdom market model, there are two ways for ES to participate in the energy market: the first is to buy or sell power in advance through bilateral negotiations or exchange trading and to submit a power plan in advance; the second is to participate in the real-time balancing market, relying on its flexibility to provide upward volume to meet potential power shortages and low volume to help renewable energy consumption (Energy Storage News, 2021). In terms of auxiliary services, the United Kingdom has also established various products, including enhanced fast frequency regulation, fast frequency regulation, short-term operation backup, and fast backup (National Grid, 2016). Like the US market, Australia also has trading targets for energy and ancillary services for ES to realize value. In China, the 14th Five-Year Plan for Renewable Energy Development clearly states that it is necessary to promote the large-scale application of NES, clarify the status of the independent market entity of NES, which is called independent energy storage (IES), and improve the trading mechanism and technical standards for ES to participate in various power markets. The National Development and Reform Commission and the National Energy Administration jointly issued a notice on further promoting the participation of new energy storage in the electricity market and dispatching applications (Document 475), which specifies the technical, dispatching and operational conditions that IES should have and encourages the NES that exists in the form of co-construction with new energy generation unit, to turn into IES through technical transformation. In response to the call, Shandong, Guangdong, Fujian, and other provinces have made meaningful attempts in ES market participation, among which Shandong's ES market participation mechanism is at the forefront of the country.

For the province studied in this paper, by the end of April 2022, the total scale of NES that has been put into operation is 111 MW, of which 93 MW/1 h of ES is built for renewable energy stations. Its 14th Five-Year Plan for Energy Development proposes further improving the energy storage and transportation network and making several centralized electrochemical ES power plants. However, there is currently no way in the province to enable IES to participate in the electricity market. Establishing a corresponding market

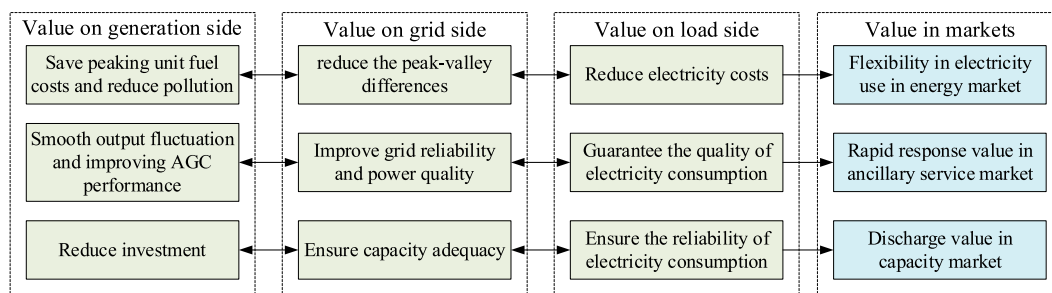


FIGURE 1
Value manifestation of energy storage for different market entities.

mechanism and analyzing the operation strategy and profitability is urgent.

In response to the national policy and strategy of encouraging the development of NES, this paper studies how IES participates in the market based on the growth of the electricity market in a provincial region in China. IES's profitability is calculated, and the operation strategy is analyzed to provide a theoretical basis for developing IES in this province. The main contributions are as follows.

- (1) Based on the current and future development of the electricity market in a province in China, Mechanisms for IES to participate in various types of electricity markets are designed.
- (2) According to the situation and model of the IES in the province, the costs required to be recovered are calculated. The strategies for the current and future participation of IES in various types of markets by division time or capacity are developed, and the profits for each participation scenario are calculated.
- (3) The numerical simulation results provide theoretical analysis for the development and formulation of policies of IES in the province.

The remainder of this paper is organized as follows. [Section 2](#) describes the designed participation mechanisms of IES in current and future electricity markets. [Section 3](#) presents the detailed calculation method of the profitability in every market. [Section 4](#) presents the numerical simulation results, and the policy recommendations are proposed in [Section 5](#).

2 Participation mechanism of independent energy storage in electricity market

2.1 Value and role in electricity market

Based on its physical characteristics, NES realizes many potential values in power systems. The exact value has

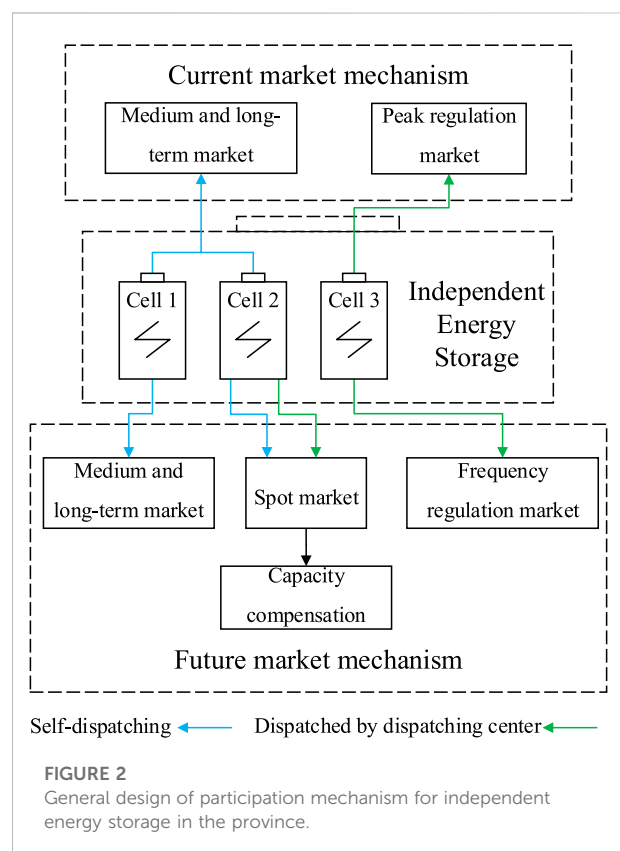


FIGURE 2
General design of participation mechanism for independent energy storage in the province.

different manifestations for market entities, as shown in [Figure 1](#). Therefore, it can provide corresponding bids in several types of electricity markets in the province. Because of its storage capacity, it can reduce the peak-valley differences in the system, thus saving fuel and start/stop costs of peak load units. Since ES can discharge, it can act as capacity support and reduce a portion of the investment in the generation units. NES has the advantages of fast response, flexible configuration and short construction cycle, which can play various roles in power system operation such as peak, peak regulation, frequency

regulation, ramp climbing and black start, and is an essential part of the new power system. Therefore, the conclusion of the above is that IES can participate in the energy market, the ancillary service market, and the capacity compensation of the province and bring into play the integrated value of ES to obtain multiple revenues.

2.2 Unified principles for design of participation mechanism

In terms of participation time, based on the actual development of the electricity market in the province, the participation mechanism is designed according to the current and future market mechanisms and the types of markets are shown in [Figure 2](#), respectively.

In terms of dispatching, IES can be designed to participate in the medium and long-term market and spot market in the self-dispatching mode, and can also be designed to participate in the spot market, peak regulation market and frequency regulation market in the mode that is dispatched by dispatching centre of the province.

IES can independently choose the type of market to participate in. When choosing to participate in multiple types of markets at the same time, it is required to partition its total capacities, the initial state of charge according to the number of metering and control devices and the capabilities of individual cells, and submit and participate in different markets as different market entities, respectively.

For the co-constructed NES configured off-site in the province, when it meets the technical conditions and requirements of IES, it can participate in the electricity market as IES.

2.3 Current mechanism design for independent energy storage participation

Document 475 pointed out that to accelerate the participation of IES in the electricity market for peak regulation and to accelerate the involvement of IES in the medium and long-term market and spot market. Currently, the province's medium and long-term market and peak regulation market are well developed, and the market system is mature, which provides a favourable market environment for the participation of IES.

Currently, the call of ES in the province is for administrative services only, and the electricity purchase and generation prices align with the large industrial and benchmark electricity prices, respectively.

2.3.1 Mechanism design for participation in medium and long-term market

As one of the new market entities to participate in intra-provincial trading, IES can be involved in monthly and D-3

trading, required to follow the rights and obligations of new market entities within the medium and long-term market rules. In addition, when IES declares power for each period in self-dispatch mode, it is required to be responsible for managing the state of charge by itself. The declared power for all periods must meet the physical constraints of the ES equipment.

2.3.1.1 Monthly trading

In principle, IES can only declare the amount of charging or discharging in the same trading period. IES does not participate in the first 30 minutes of the call auction phase. If the call auction phase is over and trading prices for electricity are formed, IES can only be listed operationally. Otherwise, it needs to wait for the matchmaking phase after. IES takes priority over the grid entity to participate in the market as a price taker by quoting electricity without quoting the price. The units in the market bear the uncontracted charging amount in equal proportion to their remaining capacities, and the grid entity takes the uncontracted discharging amount. Generation entities and users delist the listed charging and discharging amounts of IES during trading hours.

2.3.1.2 D-3 trading

IES only conducts listing operations and can act as either additional listing or reduced listing, which means that it is given priority to participate in the market clearing as a price taker by quoting electricity without quoting a price in the D-3 trading. Generation entities and users do delisting operations on the listed electricity of IES within trading hours.

2.3.2 Mechanism design for participation in peak regulation market

This mechanism applies to independent electrochemical energy storage stations with a power capacity of 5 MW and a continuous discharge time of 1 h or more, which the provincial power dispatching centre directly dispatches. Other NES (flywheel, compressed air, *etc.*) stations can refer to this standard. IES is subject to the rights and obligations of market entities.

IES only declares the electricity, which is dispatched preferentially when the coal-fired units run below 50% for peak regulation. The charging electricity of IES is compensated according to the upper limit of the second level of the quotation of coal-fired units in deep peak regulation. When there are multiple IESs for declaration, the day-ahead clearing is carried out according to the order of charging rates from high to low. When the actual deep peak regulation demand of the system is higher (or lower) than the day-ahead clearing result, IES is dispatched (or stopped) in order of charging rate from high to low (or from low to high). When the charging rates of IESs are the same, these IESs will be sorted according to the order of declaration.

The provincial power dispatching centre shall dispatch the IESs discharge before 17:00 the next day on each dispatch day to restore it to the initial states of charge. The IESs shall not participate in other market operations on the next day.

2.4 Future mechanism design for independent energy storage participation

In the future market mechanism, IES will participate in the medium and long-term market in the same way as in the current market mechanism.

2.4.1 Mechanism design for participation in spot market

IES is subject to the rights and obligations of market entities in the spot market, which consists of day-ahead and real-time trading floors (Philpott and Pettersen, 2006; Xiao and Chen, 2020). The charging power is tentatively set at no less than 5 MW, and the continuous charging time is not less than 1 h. There are two optional participation methods for IES. One is to prioritize clearing by self-dispatching, and the other is to completely hand over the operation control and the unified dispatching method to the dispatching centre.

2.4.1.1 Day-ahead spot trading

When the self-dispatching method is selected, IES declares the working day's self-dispatching curve without quoting, gives priority to clearing, and accepts the spot market price.

When the unified dispatching method is selected, the power dispatching centre formulates an IES charging and discharging plan according to the pre-clearing price after the optimization calculation by the Security Constrained Unit Combination (SCUC) program and adds the plan to the Security Constrained Economic Dispatch (SCED) program as a boundary condition optimization calculation, and clears to get the trading result.

2.4.1.2 Real-time spot trading

IES, which chooses the unified dispatching method, can participate in real-time spot trading. During real-time operation, the power dispatching centre formulates the IES charging and discharging plan based on the real-time market nodal price curve and the real-time state of charge and adds the plan to the SCED program as one of the operating boundary conditions for rolling market clearing calculation.

2.4.2 Mechanism design for participation in frequency regulation market

Similar to the market above participation requirements, IES is subject to the rights and obligations of market entities in the frequency regulation market. The charging power is set at not less than 5 MW and the continuous charging time is not less than 1 h.

When the spot market is operating, IES, which participates in both the frequency regulation market and the spot market, can obtain the frequency regulation mileage compensation and the frequency regulation capacity compensation. In contrast, IES, which only participates in the frequency regulation market, can only get the frequency regulation mileage compensation. The ranked prices of

each market entity are equal to its declared price divided by its comprehensive performance indicator on the previous trading day.

2.4.3 Mechanism design for participation in capacity compensation

At the early stage of spot market operation, the capacity compensation mechanism is implemented for the non-constructed IES to ensure reasonable cost recovery of ES equipment. The participation requirements for IES are the same as those for the spot market.

At this stage, IES is treated as a power generation source and enjoys the same capacity compensation unit price as the generation units, which is taken as the average of the capacity compensation price of each unit.

3 Operation strategy and profit ability analysis of independent energy storage

3.1 Cost of new energy storage system

In the actual use of the ES system, it is necessary to support critical systems such as the power conversion system (PCS), energy management system (EMS) and monitoring system. Among them, PCS, as the vital part of the ES system, can realize the bidirectional energy flow between the ES device and the AC power grid; EMS is responsible for monitoring the operating of the ES system and determining the optimal charging and discharging strategy of the ES.

Therefore, the cost of an NES system is divided into two categories: the first is the initial investment cost, including the cost of configuring a specific capacity of ES, called capacity cost, and the cost of including PCS, EMS and other monitoring hardware equipment, called the power cost; the second is the operation and maintenance cost during the annual operation.

3.1.1 Initial investment cost

The initial investment cost of IES (S_{ii}) is determined according to the winning price of the engineering procurement construction (EPC) of the ES station in recent years, as shown below.

$$S_{ii} = C_{EPC}E \quad (1)$$

where C_{EPC} is the EPC's winning unit price; E is IES's energy capacity.

3.1.2 Annual operation and maintenance cost

The annual operation and maintenance cost (S_{aom}) is mainly related to the capacity of the ES system and has remarkable differences under different capacities.

$$S_{aom} = C_{aom}E \quad (2)$$

where C_{aom} is the annual operation and maintenance cost per unit capacity of IES.

3.1.3 Annual cost

Considering the service life and benchmark rate of return (ie) of the ES system, the initial investment cost is amortized over the life cycle (T) and superimposed with the annual operation and maintenance cost to obtain the annual cost (AC), which is shown below.

$$AC = \frac{ie(1+ie)^T}{(1+ie)^T - 1} C_{EPC}E + C_{aom}E \quad (3)$$

3.2 Parameter processing

In this paper, the most widely used electrochemical ES in NES is taken as the main research object, and the following parameters are calculated.

3.2.1 Average annual available capacity

The impact of the capacity decay of the ES batteries is evenly spread over the life cycle to obtain the average annual available capacity (E_{aa}), shown below.

$$E_{aa} = \frac{\left[\frac{T}{T_r}\right] \sum_{i=0}^{T_r-1} E(1-r_d)^i + \sum_{i=0}^{T-1-\left[\frac{T}{T_r}\right] T_r} E(1-r_d)^i}{T} \quad (4)$$

where T_r is the battery replacement period; r_d is the annual battery capacity decay rate; $[\cdot]$ is the upward rounding operation; and i is the index.

3.2.2 Average annual continuous discharge time

The continuous discharge time represents the capacity value of ES to a certain extent. After considering the battery capacity decay and the depth of discharge (r_{dd}), the average annual continuous discharge time (T_{cd}) can be obtained, as shown in the following equation.

$$T_{cd} = \frac{E_{aa} r_{dd}}{P} \quad (5)$$

where P is the power capacity of ES.

3.2.3 Average annual operation and maintenance cost

The battery replacement cost is spread over the life cycle and as part of the annual operation and maintenance cost to obtain the average annual operation and maintenance cost, as follows.

$$S_{aom} = S_{aom} + \frac{\left[\frac{T}{T_r}\right] C_{br}E}{T} \quad (6)$$

where C_{br} is the battery price per unit capacity. Therefore, the annual cost is modified to be expressed as follows.

$$AC = \frac{ie(1+ie)^T}{(1+ie)^T - 1} S_{ii} + S_{aom} \quad (7)$$

3.2.4 Revenue conversion ratio

Considering the planned downtime due to maintenance and the unplanned downtime due to failure during the life cycle of ES, the revenue conversion ratio (r_c) can be obtained as shown below, which is the ratio of the actual benefit of ES to the ideal benefit without considering downtime.

$$r_c = 1 - r_{dt} \quad (8)$$

where r_{dt} is the forced downtime rate.

3.3 Current operation strategy and profit ability analysis

3.3.1 Participation in peak regulation market

IES is prioritized for dispatch in the peak regulation market, resulting in the following expression for the peak regulation amount of IES on day i ($Q_{pr,i}$).

$$Q_{pr,i} = \min(E_{pr,i} r_{dd}, Q_{pd,i}) \quad (9)$$

where $E_{pr,i}$ and $Q_{pd,i}$ are the capacity participating in peak regulation and the peak regulation demand on day i , respectively.

According to the designed mechanism for IES to participate in the peak regulation market, the upper limit of the second level of the quotation of coal-fired units in deep peak regulation is taken as the compensatory unit price (C_{pr}). The expression for the annual profit of participation in the peak regulation market (p_{pr}) is as follows.

$$p_{pr} = r_c \sum_i^{N_{pr}} C_{pr} Q_{pr,i} \quad (10)$$

where N_{pr} is the number of days that IES participates in the peak regulation market for the year.

3.3.2 Participation in medium and long-term market

IES has a minimal capacity relative to other market entities and is prioritized for clearing as a price taker in the province, so it is assumed that its participation does not affect the clearing price in the energy market. When IES is fully charged and fully discharged, The expression for the annual profit of participation in the medium and long-term market (p_{ml}) is as follows.

$$p_{ml} = r_c \sum_i^{N_{ml}} E_{ml,i} r_{dd} (\eta_{cd} C_{ml,dis,i} - C_{ml,ch,i}) \quad (11)$$

where N_{ml} is the number of days that IES participates in the medium and long-term market for the whole year; $E_{ml,i}$, $C_{ml,ch,i}$ and $C_{ml,dis,i}$ are the capacity participating in the medium and long-term market, the charging price and the discharging price in

the medium and long-term market on day i , respectively; η_{cd} is the charge-discharge efficiency of IES.

IES can be set to charge in the valley hours and discharge in the sharp or peak hours. When IES participates in the energy market in the self-dispatching mode, its charging price is not exempt from transmission and distribution prices, governmental funds and surcharges. Therefore, the expressions of charging and discharging price of IES in the medium and long-term market can be obtained as follows.

$$C_{ml, ch, i} = C_{ml, v, i} + C_{td, i} + C_{gs, i} \quad (12)$$

$$C_{ml, dis, i} = \begin{cases} C_{ml, s, i}, & i \in D_s \\ C_{ml, p, i}, & i \in D_p \end{cases} \quad (13)$$

where $C_{td, i}$, $C_{gs, i}$ are the transmission and distribution prices, governmental funds and surcharges on day i , respectively; $C_{ml, v, i}$, $C_{ml, s, i}$ and $C_{ml, p, i}$ are the valley price, sharp price and peak price on day i , respectively; D_s and D_p are the sets of days with and without sharp hours, respectively.

3.4 Future operation strategy and profit ability analysis

3.4.1 Participation in spot market

Consistent with the relevant analysis of participation in the medium and long-term market, the expression for the annual profit of participation in the spot market (p_{sp}) is as follows.

$$p_{sp} = r_c \sum_i^{N_{sp}} E_{sp, i} r_{dd} (\eta_{cd} C_{sp, dis, i} - C_{sp, ch, i}) \quad (14)$$

where N_{sp} is the number of days that IES participates in the spot market for the whole year; $E_{sp, i}$, $C_{sp, ch, i}$ and $C_{sp, dis, i}$ are the capacity participating in the spot market, the charging price and the discharging price in the spot market on day i , respectively.

It can be assumed that IES is charged during the lowest price hours and discharged during the highest price hours in the spot market. Document 475 states that when the dispatching centre dispatches ES, its charging power does not bear transmission and distribution price and governmental funds and surcharges. Therefore, the expressions of charging prices for participating in the spot market in the self-dispatching mode ($C_{sp, sd, ch, i}$) and in the mode dispatched by the dispatching centre ($C_{sp, dc, ch, i}$), respectively, are as follows.

$$C_{sp, sd, ch, i} = C_{sp, l, i} + C_{td, i} + C_{gs, i} \quad (15)$$

$$C_{sp, dc, ch, i} = C_{sp, l, i} \quad (16)$$

where $C_{sp, l, i}$ is the lowest electricity price in the spot market on day i .

The discharge price expression for participating in the spot market is shown below.

$$C_{sp, dis, i} = C_{sp, h, i} \quad (17)$$

where $C_{sp, h, i}$ is the highest electricity price in the spot market on day i .

3.4.2 Participation in frequency regulation market

Given that the ranked price is formed in favour of frequency regulation resources with a highly comprehensive performance indicator, it is assumed that IES can be cleared.

The annual profit of participation in the frequency regulation market (p_{fr}) consists of the frequency regulation mileage compensation (p_{frmc}) and the frequency regulation capacity compensation (p_{frcc}) and is expressed as follows.

$$p_{fr} = p_{frmc} + p_{frcc} \quad (18)$$

When IES only participates in frequency regulation simultaneously, the frequency regulation mileage compensation can be obtained, but no frequency regulation capacity compensation and the corresponding expressions are as follows.

$$p_{frmc} = r_c \sum_i^{N_{fr}} \sum_t^{n_{fr, i}} D_{i, t} B_{i, t} K_{p, i, t} M_k \quad (19)$$

$$p_{frcc} = 0 \quad (20)$$

where N_{fr} is the number of days that IES participates in the frequency regulation market for the whole year; $n_{fr, i}$ is the total number of trading periods on day i ; $D_{i, t}$, $B_{i, t}$, and $K_{p, i, t}$ are the regulating mileage, clearing price and comprehensive performance indicator of ES in the period t of the day i , respectively; M_k is the regulation factor of ES, which is set to 0.7 in the province.

When IES participates in both the frequency regulation market and the spot market, additional frequency regulation capacity compensation can be obtained, and the expression is as follows.

$$p_{frcc} = r_c \sum_i^{N_{fr}} \sum_t^{n_{fr, i}} P_{fr, i, t} B_{cc} \quad (21)$$

where $P_{fr, i, t}$ is the power capacity of ES participating in frequency regulation in the period t of the day i ; B_{cc} is the unit price of frequency regulation capacity compensation in the province.

3.4.3 Participation in capacity compensation

When the non-constructed IES participates in the spot market, capacity compensation can be obtained. The expression for the annual profit of participation in the capacity compensation (p_{cc}) is as follows.

$$p_{cc} = \sum_j^{m_{sp}} C_{cc} \frac{T_{cd}}{24} \max_{i \in \Omega_j} P_{sp, i, j} \quad (22)$$

where m_{sp} is the number of months of participation in the spot market; Ω_j is the set of days in month j ; $P_{sp, i, j}$ is the maximum charging power in the spot market on day i in month j ; C_{cc} is the unit price of capacity compensation for IES, as follows.

TABLE 1 Basic parameters of independent energy storage cases.

Parameter type	Case 1	Case 2	Case 3
Characters	Off-site construction with new energy power plants	Independence	Independence
Power capacity (MW)	93	100	100
Energy capacity (MWh)	93	200	100
Life cycle (a)	25	25	25
Charge-discharge efficiency (%)	85.6	82.78	85.6
Winning price of EPC (¥/MWh)	1,930,000	1,710,000	1,930,000
Annual O&M cost (¥/MWh)	50,000	21,000	50,000
Battery replacement time period (a)	10	10	10
Battery price (¥/MWh)	900,000	800,000	900,000
Depth of discharge (%)	90	90	90
Annual battery capacity decay rate (%)	5 for year 1, 2 for years 2–10	2.5 for years 1–10, 1.7 for years 11–25	5 for year 1, 2 for years 2–10
Forced downtime rate (%)	2	2	2

$$C_{cc} = \frac{\sum C_{gc}}{n_g} \quad (23)$$

where C_{gc} is the unit price of capacity compensation for other generator sets in the spot market; n_g is the number of other generator sets in the spot market in the province.

4 Numerical simulations

4.1 Parameter setting and cost calculation of independent energy storage

4.1.1 Parameter setting

In this paper, three cases of IES are analyzed respectively, and the corresponding basic parameters are shown in Table 1. Case 1 represents all the co-constructed NES that was configured off-site in the province; Case 2 represents the first demonstration of IES in Shandong Province participating in the spot market; Case 3 is set as a comparison with most of the same parameter types as Case 1, while the characters and power capacity are the same as those of Case 2, and the energy capacity is less than that of Case2. The benchmark rate of return is taken as 8%.

4.1.2 Parameter processing and cost calculation

According to Eqs. 1–8, the costs and parameters used for the subsequent calculations of the three cases can be obtained, as shown in Table 2.

For Case 1, the initial investment cost is included in the cost of the corresponding new energy plant, so when the annual profit is greater than the average annual O&M cost, the IES of Case 1 is considered profitable. Case 2 or Case 3 is considered profitable when its annual profit exceeds the annual cost.

4.2 Current profit calculation and analysis

4.2.1 Participation in peak regulation market only

From July 2021 to June 2022, the annual statistical results of the peak regulation market profile in the province are shown in Figure 3. According to the mechanism above of participation in the peak regulation market, the peak regulation compensatory unit price is 300¥/MWh, and IES is given priority to clear.

For Case 1, the annual profit is about 5,313,193¥, which is less than its average annual O&M cost of 11,346,000¥. Therefore, only participating in peak regulation throughout the year is not profitable. The critical value of the compensatory unit price that can be profitable is 640.63¥/MWh.

For Case 2, the annual profit is about 11,304,578¥, less than its annual cost of 49,038,142¥. It is not profitable to only participate in peak regulation throughout the year. The critical value of the compensatory unit price that can be profitable is 1,301.4¥/MWh, and the number of years required to recover the initial investment cost is 6.9742.

For Case 3, the annual profit is about 5,705,232¥, less than its annual cost of 30,280,004¥. It is also not profitable to only participate in peak regulation throughout the year. The critical value of the compensatory unit price that can be profitable is 1,592.2¥/MWh, and the number of years required to recover the initial investment cost is 6.3738.

4.2.2 Participation in medium and long-term market only

According to the statistics of the average monthly settlement electricity price of the province for four periods from July 2021 to June 2022, the 5 months containing the sharp periods are January, July, August, September and December, and the sharp and valley spread or peak-valley spread for the 12 months is shown in Figure 4. The annual average peak

TABLE 2 Costs and parameters of independent energy storage cases.

Data type	Case 1	Case 2	Case 3
Initial investment cost (¥)	179,490,000	342,000,000	193,000,000
Average annual O&M cost (¥)	11,346,000	17,000,000	12,200,000
Annual cost (¥)	28,160,404	49,038,142	30,280,004
Average annual available capacity (MWh)	85.5848	184.3868	92.0267
Average annual continuous discharge time (h)	0.8282	1.6595	0.8282
Revenue conversion ratio (%)	98	98	98

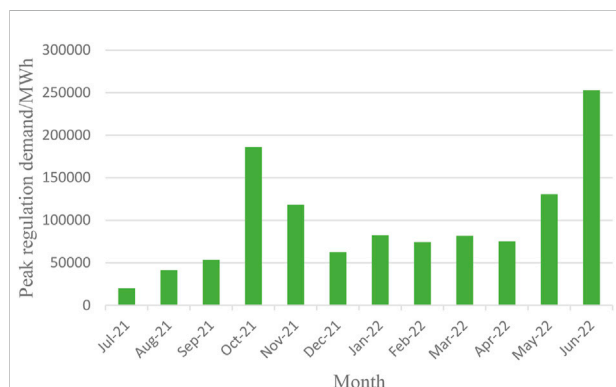


FIGURE 3

Monthly peak regulation demand of the provincial power system from July 2021 to June 2022.

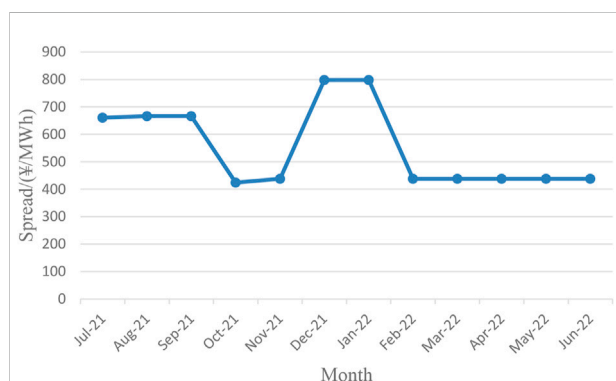


FIGURE 4

Average monthly sharp and valley or peak-valley spread for the province from July 2021 to June 2022.

price and peak-valley spread are about 836.48¥/MWh and 553.49¥/MWh, respectively.

As with the relevant data of large industrial power supply of 35 kV level, the transmission and distribution price and the governmental funds and surcharges for IES are set at 0.1585¥/kWh and 0.0268¥/kWh, respectively.

For Case 1, the annual profit is about 6,863,694¥, which is less than its average annual O&M cost of 11,346,000¥. Therefore, it is not profitable to only participate in medium and long-term market throughout the year. The annual average peak price that can be profitable when the annual average valley price is constant is 1,028.1¥/MWh.

For Case 2, the annual profit is about 13,384,642¥, less than its annual cost of 49,038,142¥. It is not profitable to only participate in medium and long-term market throughout the year. The annual average peak price that can be profitable when the annual average valley price is constant is 1,563.7¥/MWh, and the number of years required to recover the initial investment cost is 6.9742.

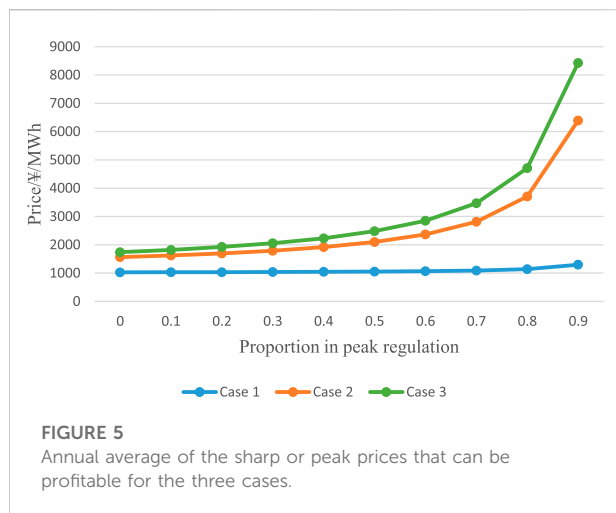
For Case 3, the annual profit is about 7,380,317¥, less than its annual cost of 30,280,004¥. It is also not profitable to only participate in medium and long-term market throughout the year. The annual average peak price that can be profitable when the annual average valley price is constant is 1,741.1¥/MWh, and the number of years required to recover the initial investment cost is 6.3738.

4.2.3 Participation in medium and long-term and peak regulation markets

4.2.3.1 Participation by division time

IES is set to participate in the medium and long-term market in the 5 months that contain sharp periods and in the peak regulation market in the other months. Given the above calculation results are not profitable and there is a particular gap between profitability, the compensatory unit price is set to the upper limit of the fifth level of the quotation of coal-fired units, which is 600¥/MWh, to calculate the profitability and the conditions required for profitability in the medium and long-term market.

For Case 1, the annual profit is about 11,936,084¥, which is greater than its average annual O&M cost of 11,346,000¥. Therefore, participating in the medium and long-term market and peak regulation by division time throughout the year is profitable. The profit in the medium and long-term market is about 4,483,851¥, and the profit in the peak regulation market is about 7,452,234¥.



For Case 2, the annual profit is about 24,929,462¥, less than its annual cost of 49,038,142¥. Participating in the medium and long-term market and peak regulation by division time throughout the year is not profitable. The average peak price that can be profitable when the average valley price is constant is 2,164.9¥/MWh. The profit in the medium and long-term market is about 8,972,242¥, and the profit in the peak regulation market is about 15,957,220¥.

For Case 3, the annual profit is about 12,829,252¥, less than its annual cost of 30,280,004¥. Participating in the medium and long-term market and peak regulation by division time throughout the year is also not profitable. The average peak price that can be profitable when the average valley price is constant is 2,639.2¥/MWh. The profit in the medium and long-term market is about 4,821,345¥, and the profit in the peak regulation market is about 8,007,907¥.

4.2.3.2 Participation by division capacity

IES will participate in peak regulation and medium and long-term markets throughout the year. The proportion of participation in peak regulation, whose value is from 0 to 0.9, and the regulation accuracy is 0.1. The compensatory unit price is still set at 600¥/MWh.

The annual average of the sharp or peak prices that can be profitable for the three cases at a constant annual average valley price (263¥/MWh) is shown in Figure 5.

For the three cases, IESs are not profitable, and as the value of r_c increases, the sharp or peak prices for IESs to be profitable also increase gradually.

4.2.4 Results analysis

The above-mentioned situations of only participating in the medium and long-term market, peak regulation market, and participating by division time are summarized as shown in Table 3.

Case 1 can only be profitable when participating in the markets by division time, but all the calculation results in the other two cases are not profitable. Therefore, the participation by division time can take advantage of the characteristics of the respective time distributions of the medium and long-term and peak regulation markets, which is most beneficial for IES.

According to the current development of the medium and long-term market in the province, when participating in the medium and long-term market only, the annual average peak prices that can be profitable are significantly higher than the actual annual average peak price in all three cases. The reason is that the peak-valley spread is not large enough and that the transmission and distribution price and the governmental funds and surcharges occupy a particular profit margin.

According to the current development of the peak regulation market in the province, the number of trades conducted throughout the year is small, and the daily peak regulation demand varies greatly, resulting in a low utilization rate of IES in the peak regulation market. Therefore, when Cases 2 and 3 only participate in peak regulation, significantly high compensatory prices (1,301.4¥/MWh, 1,592.2¥/MWh) is required to recover the cost.

According to the results of participation by division capacity, it is clear that the annual medium and long-term market is more favourable to IES than the annual peak regulation market. The higher the sharp or peak price that can be profitable when participating in the medium and long-term market only, the faster the sharp or peak price that can be profitable increases with the increase of r_c .

4.3 Future profit calculation and analysis

4.3.1 Participation in medium and long-term market only

For the future medium and long-term market that has not yet been carried out in the province, the prices for the sharp, peak and valley periods are taken as their latest price ceilings, respectively, and the valley price is 161.8¥/MWh. The values of the sharp and peak prices are taken in two ways depending on the implementation scheme: 1) with a peak-to-valley price ratio of 3:1, the sharp price is 1,033.6¥/MWh, and the peak price is 832.4¥/MWh; 2) with a peak-to-valley price ratio of 4:1, the sharp price is 1,435.9¥/MWh, and the peak price is 1,167.7¥/MWh.

4.3.1.1 Peak-to-valley price ratio of 3:1

For Case 1, the annual profit is about 12,070,679¥, which is greater than its average annual O&M cost of 11,346,000¥. Therefore, it is profitable to only participate in medium and long-term market throughout the year.

For Case 2, the annual profit is about 24,469,976¥, which is less than its annual cost of 49,038,142¥. It is not profitable to only participate in medium and long-term market throughout the

TABLE 3 Summary of profit of participation in current electricity markets.

Current analysis		Profit (¥)	Cost to be recovered (¥)	Profitable or not	Critical value of peak or compensation price (¥/MWh)
Peak regulation only	Case 1	5,313,193	11,346,000	No	640.63
	Case 2	11,304,578	49,038,142	No	1,301.4
	Case 3	5,705,232	30,280,004	No	1,592.2
Medium and long-term market only	Case 1	6,863,694	11,346,000	No	1,028.1
	Case 2	13,384,642	49,038,142	No	1,563.7
	Case 3	7,380,317	30,280,004	No	1,741.1
Participation by division time	Case 1	11,936,084	11,346,000	Yes	\
	Case 2	24,929,462	49,038,142	No	2,164.9
	Case 3	12,829,252	30,280,004	No	2,639.2

TABLE 4 Critical values of discharging price and charging-discharging spread in self-dispatching mode.

Self-dispatching		Charging price (¥/MWh)				Capacity compensation profit (¥)
		100	200	300	400	
Critical value of discharging price (¥/MWh)	Case 1	814.37	931.19	1,048.01	1,164.83	0
	Case 2	1,019.90	1,140.70	1,261.50	1,382.31	15,857,726
	Case 3	1,215.21	1,332.04	1,448.86	1,565.68	7,914,528
Critical value of spread (¥/MWh)	Case 1	714.37	731.19	748.01	764.83	0
	Case 2	919.90	940.70	961.50	982.31	15,857,726
	Case 3	1,115.21	1,132.04	1,148.86	1,165.68	7,914,528

TABLE 5 Critical values of discharging price and charging-discharging spread in the mode of dispatched by the dispatching center.

Dispatched by dispatching center		Charging price (¥/MWh)				Capacity compensation profit (¥)
		100	200	300	400	
Critical value of discharging price (¥/MWh)	Case 1	597.90	714.72	831.54	948.36	0
	Case 2	796.05	916.86	1,037.66	1,158.46	15,857,726
	Case 3	998.74	1,115.56	1,232.39	1,349.21	7,914,528
Critical value of spread (¥/MWh)	Case 1	497.90	514.72	531.54	548.36	0
	Case 2	696.05	716.86	737.66	758.46	15,857,726
	Case 3	898.74	915.56	932.39	949.21	7,914,528

year. The annual average peak price that can be profitable when the annual average valley price is constant is 1,417.3¥/MWh.

For Case 3, the annual profit is about 12,979,225¥, less than its annual cost of 30,280,004¥. It is also not profitable to only participate in medium and long-term market throughout the year. The annual average peak price that can be profitable when the annual average valley price is constant is 1,599.5¥/MWh.

4.3.1.2 Peak-to-valley price ratio of 4:1

For Case 1, the annual profit is about 20,645,367¥, which is greater than its average annual O&M cost of 11,346,000¥. Therefore, it is profitable to only participate in medium and long-term market throughout the year.

For Case 2, the annual profit is about 42,334,973¥, which is less than its annual cost of 49,038,142¥. It is not profitable to only

TABLE 6 Critical values of discharging price and charging-discharging spread.

Dispatched by dispatching center			Charging price (¥/MWh)				Capacity compensation profit (¥)	Profit in medium and long-term market (¥)
			100	200	300	400		
Peak-to-valley price ratio of 3:1	Critical value of discharging price (¥/MWh)	Case 1	490.58	607.40	724.22	841.05	0	6,250,219
		Case 2	1,079.02	1,199.82	1,320.62	1,441.43	9,083,585	12,735,679
		Case 3	1,414.61	1,531.43	1,648.25	1,765.08	4,533,581	6,720,665
	Critical value of spread (¥/MWh)	Case 1	390.58	407.40	424.22	441.05	0	6,250,219
		Case 2	979.02	999.82	1,020.62	1,041.43	9,083,585	12,735,679
		Case 3	1,314.61	1,331.43	1,348.25	1,365.08	4,533,581	6,720,665
Peak-to-valley price ratio of 4:1	Critical value of discharging price (¥/MWh)	Case 1	196.96	313.78	430.60	547.42	0	10,253,443
		Case 2	785.40	906.20	1,027.00	1,147.80	9,083,585	21,076,227
		Case 3	1,120.99	1,237.81	1,354.63	1,471.45	4,533,581	11,025,208
	Critical value of spread (¥/MWh)	Case 1	96.96	113.78	130.60	147.42	0	10,253,443
		Case 2	685.40	706.20	727.00	747.80	9,083,585	21,076,227
		Case 3	1,020.99	1,037.81	1,054.63	1,071.45	4,533,581	11,025,208

participate in medium and long-term market throughout the year. The annual average peak price that can be profitable when the annual average valley price is constant is 1,417.3¥/MWh.

For Case 3, the annual profit is about 22,199,320¥, less than its annual cost of 30,280,004¥. It is also not profitable to only participate in medium and long-term market throughout the year. The annual average peak price that can be profitable when the annual average valley price is constant is 1,599.5¥/MWh.

4.3.2 Participation in spot market only

Given that the spot market has not yet been developed at this time, the average discharging price is set as a variable. If the charging price is fixed and the cost can be recovered, the critical value the average discharging price needs to reach is calculated in the following. The upper and lower price limits of the spot market are 0¥/MWh and 1,500¥/MWh, respectively, so the charging price is set between 100¥/MWh and 400¥/MWh, and the regulation accuracy is 100¥/MWh.

For the self-dispatching mode, the calculation results of the critical values of the discharging price and the charging-

discharging spread for the three cases are shown in Table 4. For the mode dispatched by the dispatching centre, the relevant calculation results are shown in Table 5.

4.3.3 Participation in medium and long-term and spot markets

IES is set to participate in the medium and long-term market in the months containing the sharp period and in the spot market in the remaining months in the mode dispatched by the dispatching centre. The calculation results of the critical values of the discharging price and the charging-discharging spread in the spot market are shown in Table 6.

4.3.4 Results analysis

Since the valley price ceiling for the future medium and long-term market set by the provincial government is low and the sharp and peak price ceilings are high, the peak-valley spread is widened compared to the current situation, thus making it more favourable for IES. However, Cases 2 and 3 still do not recover their costs by only participating in the medium and long-term market.

When participating in the spot market, as the set charging price increases, the cost corresponding to the charging and discharging loss increases, so the critical value of the charging and discharging spread required for profitability increases.

When IES participates in the medium and long-term and spot markets by division time, compared to the case where IES only participates in the spot market, the medium and long-term profit increases, while the time and capacity compensation for participation in the spot market decreases. For Case 1, the increased medium and long-term profit is more, and the reduced capacity compensation is 0, so the critical values are lower. Conversely, for Cases 2 and 3, the increase in medium and long-term profit is less while the decrease in capacity compensation is more, such that the critical values are higher.

Given that the frequency regulation market in the province has not yet been developed, the regulation mileage and the effect of IES cannot be reasonably estimated. Therefore, the profit calculation of IES participating in the frequency regulation market needs to be studied according to the actual operation and trading situation.

5 Conclusion

Based on the actual development of IES and electricity markets in the province, this paper designs a mechanism for IES to participate in various types of markets in the province and conducts modelling and numerical simulations on the operation strategy and profitability. The analyses and results can provide a theoretical analysis basis for developing IES and formulating policies related to IES participation in the market in the province and other regions of China. The main conclusions are as follows.

- (1) The technical cost of electrochemical IES power plants is still very high. Further research should be conducted on low-cost, high-efficiency, high-reliability and high-safety ES technologies based on different technical routes.
- (2) There is currently only the peak regulation variety in the province's auxiliary service market, and only the frequency regulation variety has been designed for the future in the province. The development of other auxiliary service trading varieties should be gradually promoted to improve the construction of the auxiliary service market while expanding the space for IES to participate in the market.
- (3) The peak-valley price spread is the key factor that dominates the profitability of ES participation in the electricity energy market and the development of user-side ES. The province should moderately widen the peak-valley price spread according to the actual situation to further support the development of user-side ES.
- (4) IES operation mechanism needs to be further optimized, and the dispatching centre needs to study the application

scenarios of ES in the power system. The IES entity needs to strengthen maintenance to improve the utilization rate of the ES.

In future research, the values of ES in electricity markets can be further explored by considering other types of participants and optimization techniques. For instance, virtual bidders can utilize energy storage to increase their profits in electricity markets (Xiao and Qiao, 2021), and stochastic dominance-based stochastic optimization (AlAshery et al., 2020) and information gap decision theory-based optimization (Li et al., 2019) can be adopted to manage the market risks for ES.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, JG; methodology, JC; original draft preparation, JG, JC, and YX; review and editing, HW, HC, and DX; supervision, DX; project administration, JG, and YX; funding acquisition, JG All authors have read and agreed to the published version of the manuscript.

Funding

National Natural Science Foundation of China (51937005).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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SPECIALTY SECTION

This article was submitted to Process and Energy Systems Engineering, a section of the journal Frontiers in Energy Research

RECEIVED 11 November 2022

ACCEPTED 25 November 2022

PUBLISHED 07 December 2022

CITATION

Li W, Liang R, Luo F, Feng S, Yang B, Liu Z, Li Z, Zhang W, Kong K and Lu S (2022), Response potential assessment of user-side flexible resources of regional power distribution networks based on sequential simulation of optimal operation.
Front. Energy Res. 10:1096046.
doi: 10.3389/fenrg.2022.1096046

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Response potential assessment of user-side flexible resources of regional power distribution networks based on sequential simulation of optimal operation

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In order to reasonably consider the support capability of multiple types of flexible resources for power grid planning and operation, this paper proposes an assessment method of response potential of end-user-side flexible resources of regional power distribution networks based on sequential simulation of optimal operation. First, the response potential evaluation framework and the evaluation index are proposed. Then, based on the idea of time series simulation of optimal operation of distribution network, the response potential evaluation model considering the interactions between flexible resources and power grid is constructed and solved by optimization package. Finally, the validity of the proposed evaluation method is verified by an actual case from a certain area in northern China. The analysis results show that the end-user-side flexible resources are a kind of balanced resources with good economy, and it is necessary to take the response potential assessment of flexible resources into account in the planning of future new type distribution networks.

KEYWORDS

new type power system, flexibility resource, response potential, demand response, sequential simulation

Introduction

Accelerating the clean and low-carbon development of energy industry and building a new type power system with increasing proportion of new energy will play a pivotal role in achieving the goal of “emission peak and carbon neutrality” in China (Han et al., 2021). Driven by the “dual-carbon” goal, the widespread accessing of flexible resources such as distributed generations, flexibly adjustable and controllable loads, energy storages and so on (Holttinen et al., 2013), will become the new normal state of the power system, which is promoting the transformation of traditional power grid planning from “source changes as

load changes” mode to “source-load interaction” mode (Andrew et al., 2013; Wang et al., 2021).

However, it is very challenging to successfully utilize new energies because of the fluctuation, intermittency and the anti-peak-regulation character of the output of the distributed generations (Ma et al., 2019), which will easily lead to the insufficient flexibility in adjustment and operation of the system, even resulting in the imbalance of power supply and demand, and posing threaten to the safe operation of the power grid in extreme cases. Through the interactive response management of flexible loads and the regulation of energy storage devices, the dynamic goal of improving the electricity consumption behavior, and peak-shaving and valley-filling can be achieved, which can provide a large amount of balance resources for the power grid and support the power balance of supply and demand (Clement-nyns et al., 2010; Muhanji et al., 2018; Dong et al., 2022). In addition, the optimal layout of power network structure and the optimal configuration of substation capacity can be realized according to the temporal and spatial distribution of flexible resources. Therefore, to some extent, the construction investment will be delayed and carbon emissions will be reduced (Mnatsakanyan and Kennedy, 2015). In order to give full play to the supporting role of flexible resources for the power balance of supply and demand in power grid planning and operation, it is necessary to make reasonable use of these resources and fully exploit the response potential of flexible resources of source-side and load-side, so as to improve the flexibility and economy of power grid operation.

The rational analysis and evaluation of the response potential of flexible resources is the precondition to explore and utilize the flexible resources effectively. Due to the wide distribution of flexible resources, the complexity of regulation and control, the diversity of construction scale and cost (Armando et al., 2010; Ulbig and Andersson, 2015), it is difficult to estimate the response capability and the response degree of flexible resources in different regions, which brings difficulties in evaluating the response potential of flexible resources. In order to assess the response potential of flexible resources, it is necessary to solve three aspects of the problems: quantitative index, evaluation model and solution method. At present, the evaluation indexes of load response degree mainly include the grid dimension indexes (Cheng and An, 2013) and the user dimension indexes (Sun et al., 2016; Ding, 2018; Zhao, 2018). Ref. (Li et al., 2015). gives an evaluation index system from three aspects: interaction participation from the user's perspective and interaction effect and security from the power grid perspective. The modeling of the potential assessment model should consider the interaction response modes between various flexible resources and power grid. The modeling of response patterns can be divided into two types: modeling based on the response characteristics of user (Huang et al., 2004; Xia et al., 2012; Pan et al., 2019) and modeling based on the optimal dispatch of power grid (Huang and Huang, 2004; Gao et al., 2014). Ref. (Luo

et al., 2020). divides flexible loads into transferable loads and reducible loads according to their response characteristics and constructs a response model. Among all kinds of analysis and evaluation methods of power system, in order to precisely simulate the increasingly complex power system, the sequential simulation optimization method has become the main research method to analyze the relevant characteristic indexes and regular patterns of power grid (Wang et al., 2013; Peng, 2019; Yang et al., 2020; Xu et al., 2022).

Based on the research results of existing block distribution network planning, this paper proposes a response potential assessment method of user-side flexible resources of regional power distribution networks. The major contributions of this paper are summarized as follows:

- 1) A series of evaluation indexes on response potential of end-user-side flexible resources are designed, which can represent the improvement degree of the system load curve and the supporting potential to the power grid planning and operation.
- 2) The response potential evaluation method based on sequential simulation of interactive operation is developed, which can describe the interactive response process between flexible resources and power grid in detail and accurately evaluate the supporting potential. The sequential simulation method takes the interactive operation mechanism of flexible resources and the power grid into account, which can better simulate the operation of the power grid in the future, thus providing more accurate guidance for the planning work.

The remainder of this paper is structured as follows: *Assessment Framework Section* introduces the evaluation framework of response potential of end-user-side flexible resources. *Evaluation Indexes of Response Potential and Interactive Response Model of Flexible Resources Section* proposes the evaluation indexes and the interactive response model of flexible resources. *Response Potential Evaluation Model and Method Based on Sequential Simulation of Interactive Operation Section* constructs the evaluation model of time series response potential to describe the interaction process between flexible resources and power grid, based on the idea of sequential simulation optimization of distribution networks operation. And the optimization software package is employed to solve the problem. *Case Study Section* presents the evaluation results of a practical example from a certain area of northern China to validate the effectiveness of the proposed model and method. *Case Study Section* concludes the paper.

The results show that the method proposed in this paper can effectively evaluate the supporting capability of the user-side flexible resources to the power grid operation, thus alleviating the operation pressure of the superior power grid, delaying the capacity construction of the superior power grid, and reducing the construction scale and investment level of the relevant power grid.

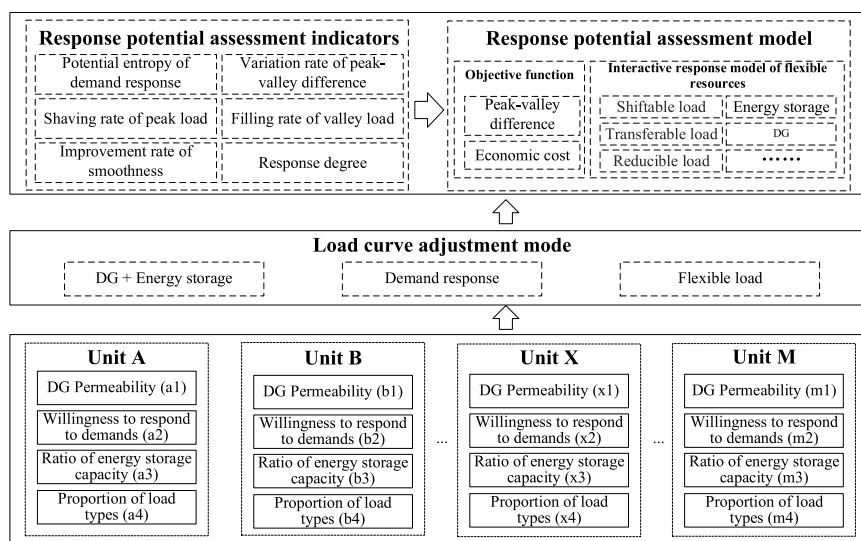


FIGURE 1
Response potential evaluation framework of flexibility resources.

Assessment framework

The block distribution network planning is the hierarchical distribution network planning at different levels based on the division and the subdivision of power supply areas into power supply zones, power supply blocks and power supply units. In recent 5 years, the block distribution network planning method has been widely used in China utilities.

In order to solve the problem of insufficient system regulation ability of different unit in different degrees, the flexible resources such as distributed generations, flexible loads and energy storage devices in the unit can be aggregated and regulated as a whole. This way can realize the balance of power supply and demand in power grid of the unit scale, and the interactive operation of power network with response participation of flexible resources can also improve the load curve of the whole system.

In this paper, the evaluation index of response potential of flexible resources is designed based on the improvement degree of system load curve characteristics and the support potential of flexible resource to power grid planning and operation. At the same time, based on the interactive response mechanism between flexible resources and power grid, a potential evaluation model based on the time series simulation and optimal operation of power grid is established, and solved by the optimization software package. Finally, the response potential of flexible resources is quantitatively analyzed based on the proposed evaluation index, which provides corresponding guidance for distribution network planning and provides basis for making rational interaction strategies.

The overall assessment framework is shown in Figure 1.

Evaluation indexes of response potential and interactive response model of flexible resources

Evaluation indexes

The flexible resource response potential defined in this paper mainly refers to the improvement degree of the system load curve and the supporting potential of the flexible resource for system planning and operations, when the flexible resource participates in the power grid interaction operation with demand response. The specific representation indexes are: potential entropy of demand response, variation rate of peak-valley difference, clipping rate of peak load, filling rate of valley load, improvement rate of smoothness and Response degree. The representation metrics and their meanings are shown in Table 1.

Potential entropy of demand response

Different categories of users have different peak-shaving and valley-filling potential. In this paper, the concept of information entropy, which describes the information quantity in information theory, is used to define the demand response potential entropy of users (Sun et al., 2016). The expression is shown in (Eq. 1).

$$PE = \frac{1}{-\sum_{i=1}^N x_i \ln x_i} \quad (1)$$

where, PE is the entropy of demand response potential, N is the number of sampling times of user load in a day, x_i is the amount of user load of the i th sample after normalization.

TABLE 1 Evaluation metrics.

Metric name	Symbol	Meaning
Potential entropy of demand response	PE	The potential for user demand response
Variation rate of peak-valley difference	H_d	The peak shaving and valley filling capacity of the flexible resource to the system
Shaving rate of peak load	H_{p-p}	The capacity of the flexible resource to shave the peak in the system
Filling rate of valley load	H_{v-v}	The capacity of the flexible resource to fill the valley in the system
Improvement rate of smoothness	S	The smoothing effect of flexible resources on system load curves
Response degree	$I_i(t)$	The response degree to which flexible resources participate in the interactive operation of the grid

Similar to information entropy describing the amount of information, demand response potential entropy can be used to describe the potential of user demand response. The more average the user's power load, the smaller the difference between peak and valley is, and the smoother the user's power consumption curve is. It can be considered that this kind of users' power consumption pattern is more regular and not easy to change, so the potential of peak shaving and valley filling is smaller, and the potential entropy is also smaller. On the contrary, for the users with large peak-valley difference and large fluctuation load curve, the regularity of power consumption is weak, so the potential of peak-shaving and valley-filling is large, and the potential entropy is also large.

Variation rate of peak-valley difference

The variation rate of peak-valley difference is defined as the ratio of the change amount of the system load's peak-valley difference when all kinds of resources participating in the demand response *versus* the system load's peak-valley difference without demand response participation. The expression is shown in (Eq. 2).

$$H_d = \frac{(P_p - P_v) - (P'_p - P'_v)}{P_p - P_v} \times 100\% \quad (2)$$

where, H_d is the variation rate of peak-valley difference; P_p and P_v are the peak value and valley value of system load without flexible resource involved, respectively; P'_p and P'_v are the peak value and valley value of the system load when flexible resources participate in demand response, respectively. The variation rate of peak-valley difference of system load represents the ability of user-side flexible resources to shave peak and fill valley of the system load. And the greater the variation rate, the stronger the ability of the peak shaving and valley filling capacity of flexible resources is.

Shaving rate of peak load

Peak shaving rate is defined as the ratio of the peak load change amount of the system when various resources participating in the demand response *versus* the peak load of the system when there is no demand response involved. The expression is shown in (Eq. 3).

$$H_{p-p} = \frac{P'_p - P_p}{P_p} \times 100\% \quad (3)$$

where, H_{p-p} is the peak shaving rate. The greater the value of H_{p-p} , the better the effect of reducing the peak load, which will help the overall load peak downward and tend to the daily average load value.

Filling rate of Valley load

The valley filling rate is defined as the ratio of the valley load change amount of the system when various resources participate in the demand response *versus* the valley load of the system when there is no demand response involved. The expression is shown in (Eq. 4).

$$H_{v-v} = \frac{P'_v - P_v}{P_v} \times 100\% \quad (4)$$

where, H_{v-v} is the valley filling rate. The greater the value of H_{v-v} , the better the valley filling effect is, which is conducive to move up the load valley value and make it tend to the daily average load value.

Improvement rate of smoothness

The smoothness improvement rate is defined as the ratio of the change amount of the standard deviation of load power within a certain period of time when various resources participate in the demand response *versus* the standard deviation of load power when there is no demand response involved. The expression is shown in (Eq. 5).

$$S = \frac{\sqrt{\frac{1}{T} \sum_{t=1}^T (P(t) - P_{ave})^2} - \sqrt{\frac{1}{T} \sum_{t=1}^T (P'(t) - P'_{ave})^2}}{\sqrt{\frac{1}{T} \sum_{t=1}^T (P(t) - P_{ave})^2}} \quad (5)$$

where, S is the smoothness improvement rate; $P(t)$ and $P'(t)$ are the active load of the system at time t without and with demand response participation, respectively; P_{ave} and P'_{ave} are the average load of the system without and with demand response participation, respectively; T is time scale, generally 24 h. S indicates the smoothing effect of the interaction response of flexible resources on the load curve. The larger the value of S , the smoother the overall load curve after interaction response.

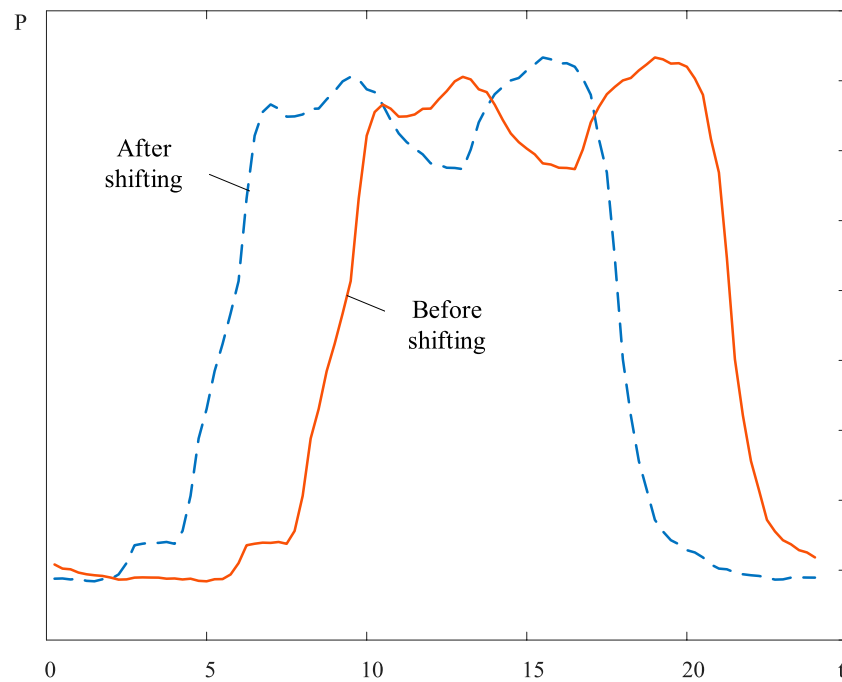


FIGURE 2
Schematic diagram of shiftable load.

Response degree

The response degree is defined as the ratio of the actual response amount of the system load to its maximum response amount. The expression is shown in (Eq. 6).

$$I_i(t) = \frac{P'_i(t) - P_{i,0}(t)}{[\gamma_{shift}(t) + \gamma_{trans}(t) + \gamma_{cut}(t)]P_{i,max}(t)} \quad (6)$$

where, $I_i(t)$ is the response degree at time t ; $P'_i(t)$ is the system load at time t with flexible resources participating in demand response; $P_{i,0}(t)$ is the system load at time t without demand response participation; $P_{i,max}(t)$ is the maximum response amount at time t that the user loads can participate in, $\gamma_{shift}(t)$, $\gamma_{trans}(t)$ and $\gamma_{cut}(t)$ are the proportion of user loads that can be shifted, transferred and reduced, respectively $[0, 1]$. $I_i(t)$ described the actual level of user loads' participation in demand response at time t , which is closely related to the power consumption characteristics of the load, the interaction mechanism of the dispatch center and other factors.

Interactive response model of flexible resources

Interactive response model of user-side flexible load

User load can be classified into industrial load, commercial load, residential load and so on. According to the response

characteristics, user-side flexible load can be divided into shiftable load, transferable load and reducible load.

Shiftable load

The shiftable load mainly refers to the load that the regular pattern of electricity consumption cannot be changed, but can only be shifted on the time axis. The shiftable load is mainly the industrial load with adjustable shifts. The load curve can be shifted by adjusting its power consumption time without changing its power consumption shape. The schematic diagram of the shiftable load is shown in Figure 2.

The interactive response model of shiftable load participating in power grid operation is shown in (Eq. 7):

$$\begin{cases} P_{shift}(t) = (1 - \alpha \times \gamma_{shift})P_{L0}(t) \\ P_{shift}(t + \Delta t) = P_{L0}(t + \Delta t) + (\alpha \times \gamma_{shift}) \times P_{L0}(t) \end{cases} \quad (7)$$

where, $P_{shift}(t)$ is the load at time t after shifting; $P_{L0}(t)$ is the load before it participates in the demand response; α is the proportion of load shifted at time t into time $t + \Delta t$.

Transferable load

Transferable load refers to a kind of load that can transfer part of the load in peak period to the valley period. For example, household appliances, such as water heaters and air conditioners in residential loads, can achieve peak-shaving and valley-filling

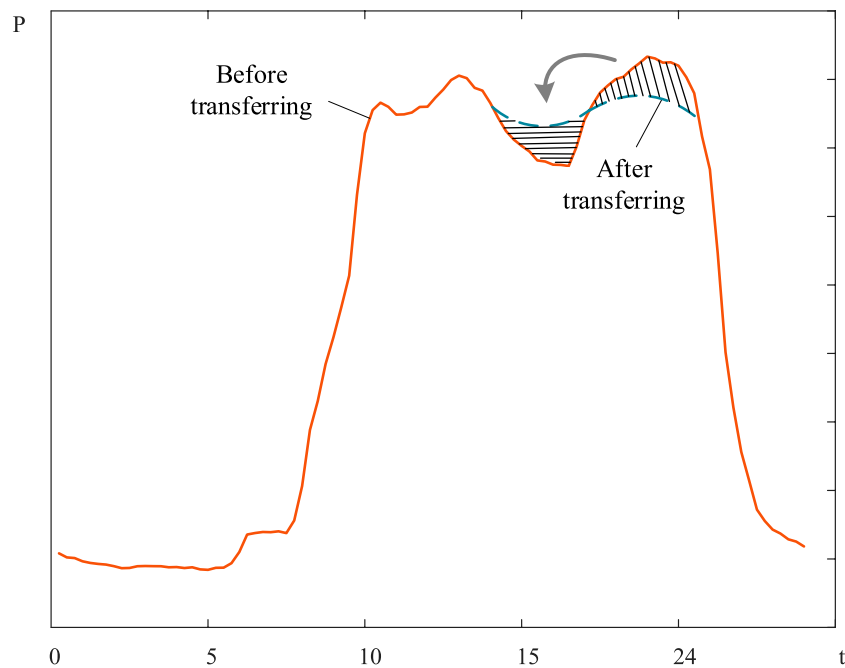


FIGURE 3
Schematic diagram of transferable load.

response by adjusting their operation time. Figure 3 shows a schematic diagram of the transferable load.

The interactive response model of transferable load participating in power grid is shown in (Eq. 8):

$$\begin{cases} P_{trans}(t) = [1 - \lambda_1(t) \times \gamma_{trans}(t)]P_{L0}(t) \\ P_{trans}(t + \Delta t) = P_{L0}(t + \Delta t) + [\eta(t) \times \gamma_{trans}(t)]P_{L0}(t) \end{cases} \quad (8)$$

where, $P_{trans}(t)$ is the load at time t after transferring; $\lambda_1(t)$ is the proportion of the load transferred out at time t ; $\eta(t)$ is the proportion of load transferred in at time t .

Reducible load

Reducible load means that a certain amount of load can be cut during the peak load period, so as to reduce the average power consumption. For example, commercial users' electrical appliances, such as air conditioning, refrigeration and so on, can participate the interactive response by reducing a certain output power in a short period of time, which will not affect the comfort and satisfaction of customers. The schematic diagram of the reducible load is shown in Figure 4.

The interactive response model of reducible load participating in power grid is shown in (Eq. 9):

$$P_{cut}(t) = (1 - \beta(t) \times \gamma_{cut}(t))P_{L0}(t) \quad (9)$$

where, $P_{cut}(t)$ is the load at time t after reduction; $\beta(t)$ is the proportion of user load cut at time t .

Interactive response model of energy storage

The energy storage device adjusts the system peak-valley difference by charging at the load valley period and discharging at the load peak period, so as to support and solve the supply-demand balance of the power grid. The common energy storage device is battery energy storage, whose level of stored electricity in operation is represented by state of charge (SOC). The SOC of energy storage at time t is determined by the SOC at time $t-1$ and the power of the energy storage system. The interactive response model of energy storage is shown in (Eq. 10).

$$S_i^{ESS}(t) = S_i^{ESS}(t-1) + \left(\eta_c^{ESS} P_{ic}(t) - \frac{P_{id}(t)}{\eta_d^{ESS}} \right) \frac{1}{E_i^{ESS}} \quad (10)$$

where, $S_i^{ESS}(t)$ is total electricity of the i th energy storage device at time t ; η_c^{ESS} and η_d^{ESS} are the charge and discharge efficiency of energy storage device, respectively; $P_{ic}(t)$ and $P_{id}(t)$ are the charging and discharging power of the i th energy storage device at time t , respectively; E_i^{ESS} is the rated capacity of the i th energy storage device.

Response potential evaluation model and method based on sequential simulation of interactive operation

First, the whole response potential analysis and evaluation model of the flexible resources is constructed. Then the response

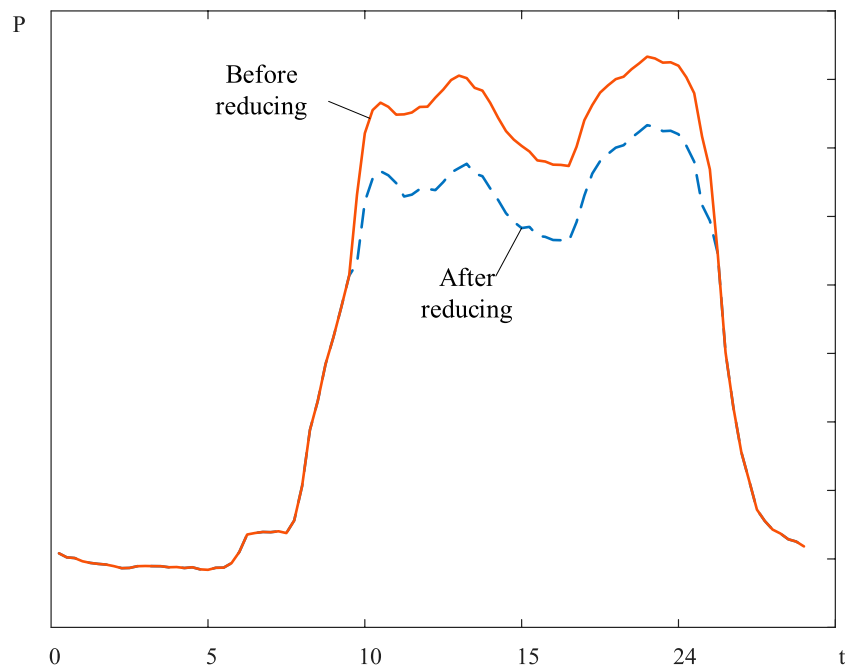


FIGURE 4
Schematic diagram of reducible load.

potential evaluation method and procedure is proposed based on the sequential simulation of interactive operation.

Response potential assessment model of flexible resources

Objective function

In this paper, the integrated optimization of the total economic cost of distribution network operation and the optimum peak-valley difference is considered as the objective. The economic cost of operation mainly includes the cost of purchasing electricity from upper power grid, the cost of load interaction and the cost of energy storage dispatching. Considering the dimensional difference of above two sub-objectives of economic cost and peak-valley difference, based on the concept of per-unit value, this paper takes the independent optimal solutions of the two sub-objectives as their respective benchmark values, and weights them as a comprehensive objective function (Yang et al., 2021). The expression of the objective function is shown in (Eqs 11–16).

$$\min F = \omega_1 \frac{F_1}{F_1^*} + \omega_2 \frac{F_2}{F_2^*} \quad (11)$$

$$F_1 = C_1 + C_{DR} + C^{ESS} \quad (12)$$

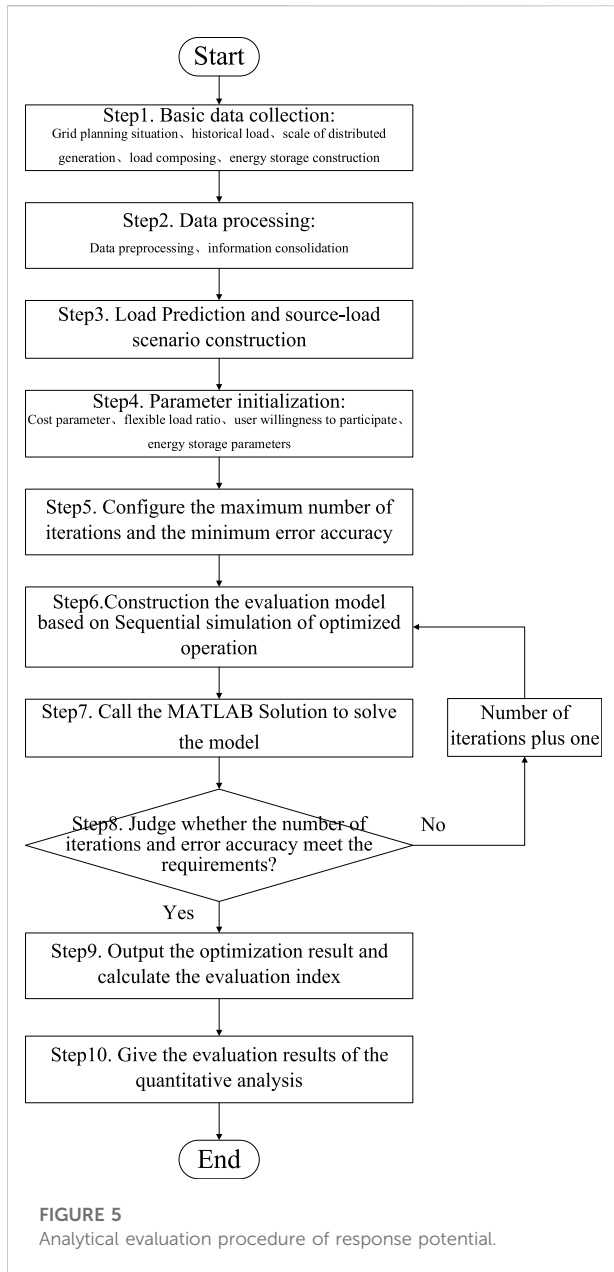
$$F_2 = \max(L(t)) - \min(L(t)) \quad (13)$$

$$C_1 = \sum_{t=1}^T \rho(t) \cdot P_1(t) \quad (14)$$

$$C_{DR} = \sum_{t=1}^T \sum_{i=1}^{N_{shift}} \rho_i^{shift}(t) \cdot \mu_i^{shift}(t) \cdot \Delta P_i^{shift}(t) + \sum_{t=1}^T \sum_{i=1}^{N_{trans}} \rho_i^{trans}(t) \cdot \mu_i^{trans}(t) \cdot \Delta P_i^{trans}(t) + \sum_{t=1}^T \sum_{i=1}^{N_{cut}} \rho_i^{cut}(t) \cdot \mu_i^{cut}(t) \cdot \Delta P_i^{cut}(t) \quad (15)$$

$$C^{ESS} = \sum_{t=1}^T \sum_{i=1}^{N_{ESS}} C_{oP_{i,ESS}}(t) \quad (16)$$

where, F_1 and F_2 are the total economic cost and the system peak-valley difference, respectively; F_1^* and F_2^* are the independent optimal solution for F_1 and F_2 , respectively; ω_1 and ω_2 are weight of F_1 and F_2 , respectively; C_1 is the cost of purchasing electricity from upper power grid; C_{DR} is the cost of load interaction; C^{ESS} is the energy storage scheduling cost; $L(t)$ is the power of the load participates in the interactive response of grid operation at time t ; $\rho(t)$ is the electricity price purchasing from upper grid at time t ; $P_1(t)$ is the output of the upper power grid at time t ; N_{shift} , N_{trans} and N_{cut} are the number of loads that can be shifted, transferred and reduced; $\rho_i^{shift}(t)$, $\rho_i^{trans}(t)$ and $\rho_i^{cut}(t)$ are the unit capacity compensation price of the i th shiftable, transferable and reducible loads at time t , respectively; $\mu_i^{shift}(t)$, $\mu_i^{trans}(t)$ and $\mu_i^{cut}(t)$ represent the response status of i th shiftable, transferable and reducible loads at time t , respectively,



which equal to 1 when participates in interactive response otherwise equal to 0; $\Delta P_i^{shift}(t)$, $\Delta P_i^{trans}(t)$ and $\Delta P_i^{cut}(t)$ are the load variation amount of the i th shiftable, transferable and reducible loads at time t , respectively; C_o is the cost coefficient of energy storage device operation and maintenance; N^{ESS} is the total number of energy storage devices; $P_{i,ESS}(t)$ is the power of the i th energy storage device at time t .

Constraints

The evaluation model needs to take into account the power balance constraints of power network, and the interaction

constraints between the source-load flexibility resources and the power grid. The details are described as follows.

The power supply and demand balance constraint

$$P_{base}(t) + \sum_{i=1}^{N_{shift}} P_{shift}(t) + \sum_{i=1}^{N_{trans}} P_{trans}(t) + \sum_{i=1}^{N_{cut}} P_{cut}(t) = \sum_{i=1}^{N^{DG}} P_i^{DG}(t) + P_1(t) - \sum_{i=1}^{N^{ESS}} \mu_{i,c} P_{i,c}(t) + \sum_{i=1}^{N^{ESS}} \mu_{i,d} P_{i,d}(t) \quad (17)$$

where, $P_{base}(t)$ is the base rigid load (the load not participating in interaction response, except the shiftable, transferable and reducible load) at time t ; N^{DG} is the number of distributed generations; $P_i^{DG}(t)$ is the output power of the i th distributed generation at time t ; $\mu_{i,c}(t)$ and $\mu_{i,d}(t)$ are the charging and discharging state of the i th energy storage device at time t , respectively, which equal to 1 when participates in interactive response otherwise equal to 0.

Distributed generation constraint

$$0 \leq P_i^{DG}(t) \leq \mu_i^{DG}(t) \cdot P_{i,max}^{DG}(t) \quad (18)$$

where, $\mu_i^{DG}(t)$ is the output signal of the i th distributed generator at time t , which equal to 1 when participates in interactive response otherwise equal to 0; $P_{i,max}^{DG}(t)$ is the maximum output power of the i th distributed generator at time t .

Flexible load constraints

$$h_i^{shift0}(t) \leq h(t) \leq h_i^{shift1}(t) \quad (19)$$

$$\mu_i^{trans}(t) \cdot \Delta P_{i,min}^{trans}(t) \leq \Delta P_i^{trans}(t) \leq \mu_i^{trans}(t) \cdot \Delta P_{i,max}^{trans}(t) \quad (20)$$

$$\Delta P_{min}^{trans} \leq \sum_{t=1}^T \Delta P_i^{trans}(t) \leq \Delta P_{max}^{trans} \quad (21)$$

$$\mu_i^{cut}(t) \cdot \Delta P_{i,min}^{cut}(t) \leq \Delta P_i^{cut}(t) \leq \mu_i^{cut}(t) \cdot \Delta P_{i,max}^{cut}(t) \quad (22)$$

$$\Delta P_{min}^{cut} \leq \sum_{t=1}^T \Delta P_i^{cut}(t) \leq \Delta P_{max}^{cut} \quad (23)$$

where, $h(t)$ is the number of hours that the shiftable load shifted; $h_i^{shift0}(t)$ and $h_i^{shift1}(t)$ are the minimum and maximum shiftable hours of the i th shiftable load at time t , respectively; $\Delta P_{i,min}^{trans}(t)$ and $\Delta P_{i,max}^{trans}(t)$ are the minimum and maximum load transfer amount of the i th transferable load at time t , respectively; ΔP_{max}^{trans} and ΔP_{min}^{trans} are the upper and lower limits of the transferable load capacity of the i th transferable load in a scheduling cycle, respectively; $\Delta P_{i,min}^{cut}(t)$ and $\Delta P_{i,max}^{cut}(t)$ are the minimum and maximum load cut amount of the i th reducible load at time t , respectively; ΔP_{max}^{cut} and ΔP_{min}^{cut} are the upper and lower limits of the reducible load capacity of the i th reducible load in a scheduling cycle, respectively.

TABLE 2 Current status of each power mesh unit and the respective forecasting loads in the planning year.

Unit	Power supply area (km ²)	Current load(MW)	Forecast load (MW)	PV capacity (MW)	Energy storage capacity(MWh)
A	1.12	16.28	28	5	2.94
B	2.15	13.18	46	10	4.96
C	6.62	82.56	118	20	19.16
D	1.79	2	20.62	3	1.79

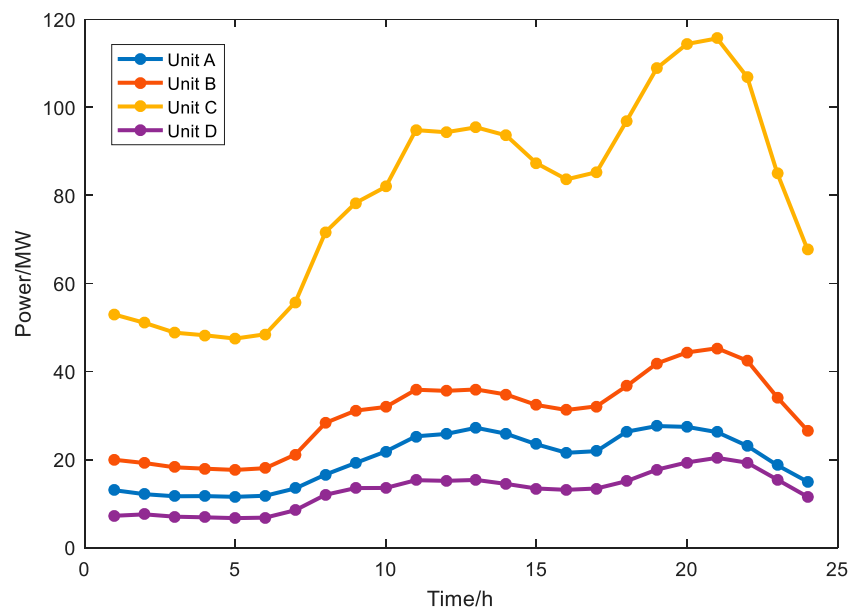


FIGURE 6
Forecast load curve of each grid (without considering flexible resources).

Energy storage device constraints

$$S_i^{ESS}(t) = S_i^{ESS}(t-1) + \eta_c^{ESS} P_{i,c}(t) - \frac{P_{i,d}(t)}{\eta_d^{ESS}} \quad (24)$$

$$E_i^{ESS} \cdot C_{i,min}^{ESS} \leq S_i^{ESS}(t) \leq E_i^{ESS} \cdot C_{i,max}^{ESS} \quad (25)$$

$$0 \leq P_{i,c}(t) \leq P_{i,max}^{ESS} \cdot \mu_{i,c}(t) \quad (26)$$

$$0 \leq P_{i,d}(t) \leq P_{i,max}^{ESS} \cdot \mu_{i,d}(t) \quad (27)$$

$$0 \leq \mu_i^c(t) + \mu_i^d(t) \leq 1 \quad (28)$$

$$S_i^{ESS}(1) = S_i^{ESS}(T) = 0.2E_i^{ESS} \quad (29)$$

where, $P_{i,max}^{ESS}$ is the rated capacity of the i th energy storage device; $C_{i,min}^{ESS}$ and $C_{i,max}^{ESS}$ are the maximum and minimum SOC values of the i th energy storage device, with values of 0.2 and 0.8, respectively.

Evaluation method

In order to describe the interactive response process between flexible resources and power grid in detail and accurately evaluate the supporting potential for power grid planning and operation, this paper adopts the analysis and evaluation idea of sequential simulation of optimized operation method.

Power system sequential simulation method (Cao et al., 2014) is to simulate the actual operation of the system at different time scales under the condition of given network topology and load level, meanwhile to analyze and evaluate the operation state and performance of the power grid are d. Based on the timing simulation method, this paper evaluates the adjustment effect of the system load by simulating the regional flexible resources' response behavior in a typical 24-h domain,

TABLE 3 Electricity price.

Time		Price (RMB/kWh)
Peak periods	10:00-14:00; 17:00-21:00	1.082
Normal periods	8:00-10:00; 14:00-17:00; 21:00-24:00	0.649
Valley periods	0:00-8:00	0.316

TABLE 4 Interactive response parameters of flexible load of each unit.

Unit	Composition of load	Transferable load proportion (%)	Reducible load proportion (%)	Willingness of participation (%)
A	Residents load 70%	10	10	30
	Commercial load 30%	10	20	20
B	Residents load 60%	10	10	20
	Commercial load 40%	10	15	15
C	Residents load 50%	15	10	20
	Commercial load 50%	5	10	20
D	Residents load 70%	15	15	30
	Commercial load 30%	5	5	20

and quantifies the response potential of flexible resources according to the evaluation index.

The objective function of the response potential assessment model mentioned above contains integer variables and non-linear terms. It is a typical mixed integer non-linear programming model. In this paper, the non-linear term of the objective function is transformed into linear description by KKT conditions (Zhang et al., 2018), and then the optimization software CPLEX is called by YALMIP in MATLAB to solve problem. A general representation of the model is shown in (Eq. 30).

$$\begin{cases} \min F(x_t) = \sum_t CO_t + OI \\ s.t. G(x_t) \leq 0 \\ H(x_t) = 0 \end{cases} \quad (30)$$

where, x_t is the variable of sequential simulation of optimized operation; CO_t is the operational cost, including electricity purchase cost, flexible load regulation cost, energy storage maintenance cost, unit operation cost and so on, as shown in (Eqs 14–16); OI is the system operation index, including system peak-valley difference, voltage deviation rate, etc., as shown in (Eq. 13); $G(\cdot)$ and $H(\cdot)$ are the inequality constraints and equality constraints of sequential simulation of optimized operation, respectively; the inequality constraints are shown in (Eqs 18–23) and (Eqs 25–28), and equality constraints are shown in (Eq. 17) and (Eq. 24).

Evaluation procedure

Figure 5 shows the analytical evaluation procedure of response potential.

Step 1: Basic data collection. To obtain the date of unit divisions, data of historical load, data of installed scale of distributed generations, data of load composition and energy storage configuration, etc., of the area to be evaluated.

Step 2: Data processing. To check and process the collected historical load data, including missing data processing, invalid data processing, outlier analysis, etc.; and to extract the efficient data from collected reports in text form.

Step 3: Load prediction and source-load scenario construction. To forecast the long-term annual load based on the historical annual load data, and to obtain the typical daily prediction load curves of all units through certain method (Luo et al., 2021). Moreover, the source-load scenario is constructed according to the output curves of regional PV and predicted load curves.

Step 4: parameter initialization. To configure the cost parameters of the evaluation mode (such as electricity purchase price, unit compensation price of flexible loads, cost parameters of energy storage, etc.), flexible load proportion, participation willingness coefficient of users, operation parameters of energy storage devices, etc.

Step 5: Configure the maximum number of iterations and minimum error accuracy. In this paper, the maximum number of

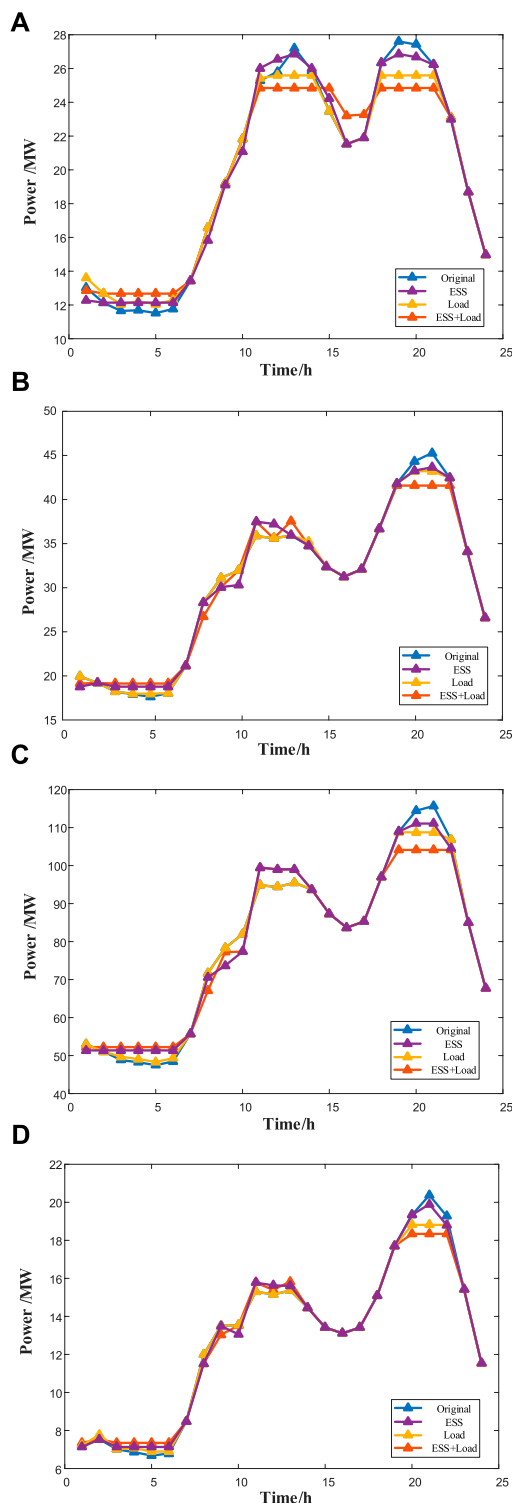


FIGURE 7
Load curve adjustment effect of four units. (A) Unit A (B) Unit B (C) Unit C (D) Unit D.

iterations is set to 50, and the minimum error accuracy of the last two optimization iterations is 10^{-6} .

Step 6: Construct the evaluation model based on sequential simulation of optimized operation.

Step 7: Call the MATLAB solution package to solve the model.

Step 8: Judge whether the number of iterations and error accuracy meet the requirements. If not, increase the number of iterations by 1 and return to step 6; otherwise, proceed to the next step.

Step 9: Output the optimization result and calculate the evaluation indexes.

Step 10: Give the evaluation results of the quantitative analysis of the flexible resources' response potential of area to be evaluated.

Case study

Case introduction

In this paper, the actual power distribution network data of a certain area in north China is taken as an example to be evaluated. This area is a type B power supply area by 10 kV distribution networks with a total planning area of 11.68 km², which contains 4 meshed and blocked power grids, numbered power mesh unit A, B, C and D, respectively.

Among 4 power meshes, Unit A is mainly used for second-class residential, administrative and commercial land; Unit B is mainly used for second-class residential and commercial land; Unit C is mainly used for second-class residential, commercial and educational land; Unit D is mainly used for residential, commercial and temple land. And the second-class residential land refers to the land planning with complete municipal public facilities, complete layout and good environments.

The current status of each power mesh unit and the respective forecasting loads in the planning year without considering the flexible resource support potential are shown in Table 2. The typical daily predicted load curves of each unit are obtained by using the method in Ref (Luo et al., 2021) based on the historical annual load of the area. Meanwhile, Figure 6 shows the typical daily load curve for each power mesh unit in the planning year without considering flexible resources.

Case calculation

In this paper, we develop 3 scenarios to quantitatively analyze the response potential of flexible resources with different levels of

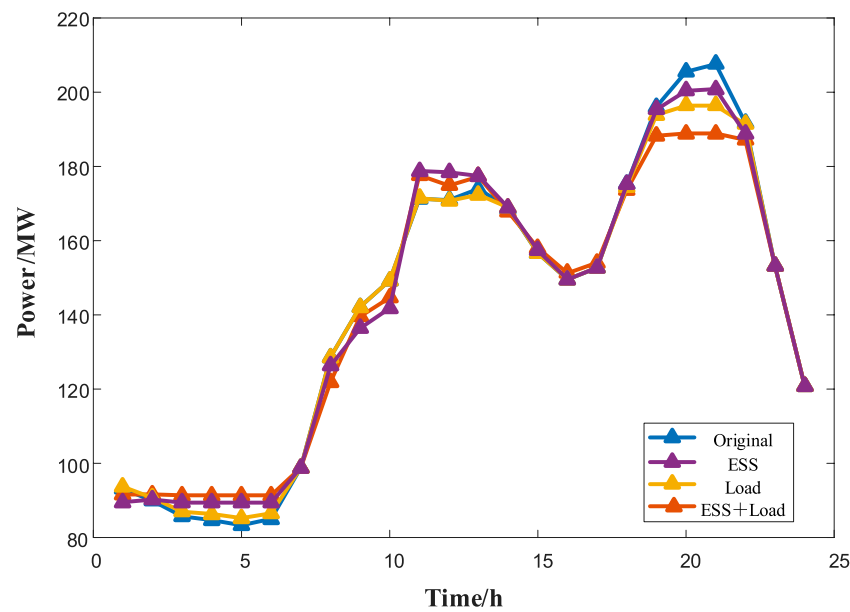


FIGURE 8

Load curve adjustment effect of whole region.

TABLE 5 Response potential assessment results.

Unit	Scenario	Potential entropy of demand response	Variation rate of peak-valley difference (%)	Shaving rate of peak load (%)	Filling rate of valley load (%)	Improvement rate of smoothness (%)
A	Scenario 1	0.2494	8.48	2.70	5.38	1.13
	Scenario 2		15.75	7.29	4.52	8.73
	Scenario 3		24.3	9.99	10.0	12.41
B	Scenario 1	0.1922	10.05	3.61	6.48	2.57
	Scenario 2		8.75	4.56	2.0	2.58
	Scenario 3		18.82	8.17	8.52	6.70
C	Scenario 1	0.1990	12.47	4.0	8.17	3.79
	Scenario 2		11.40	6.0	1.76	4.54
	Scenario 3		23.92	10.0	10.0	9.61
D	Scenario 1	0.1872	6.76	2.33	6.74	2.34
	Scenario 2		12.95	7.67	3.16	5.13
	Scenario 3		19.76	10.0	10.0	8.39
Total	Scenario 1	0.2024	10.32	3.25	7.31	3.04
	Scenario 2		10.56	5.4	2.31	4.76
	Scenario 3		21.53	9.0	9.69	9.34

demand response programs, through simulating the interaction response effect of flexible resources on the load curve under three different scenarios. These scenarios are:

- Scenario 1: only energy storage device is considered;
- Scenario 2: only flexible load regulation is considered;

Scenario 3: both energy storage and flexible load regulation are considered.

The parameters of purchase electricity price in the response potential assessment are shown in Table 3. We assume that, the reducible loads are compensated at the electricity price of the

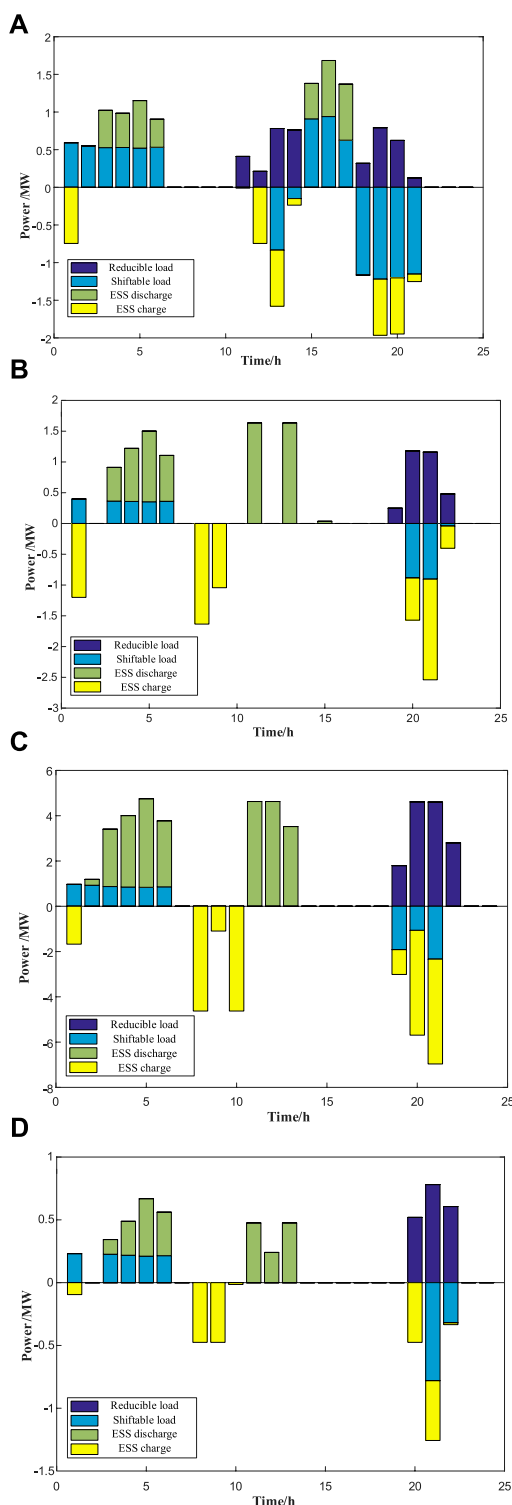


FIGURE 9
Adjustment of flexible loads and energy storage devices of each unit in scenario 3. (A) Unit A (B) Unit B (C) Unit C (D) Unit D.

load cut time, and the transferable loads are compensated at 80% of the electricity price of the load transfer time. And the operation and maintenance cost of energy storage device is set as 26 RMB/MW (Li, 2020).

The interactive response parameters of flexible loads are determined by the load composition and load characteristics in the region. For the proportion parameters of residential load, commercial load and other types of loads of the case power grid mesh units, we can set their values according to the planning land development purpose. For the parameters of the proportion of the transferable and reducible load, and the willingness of the users to participate in interactive response, they cannot be accurately captured from the usual historical load data because of not covering in the common historical load data accumulation. This paper mainly refers to relevant technical principles and literature data (Li et al., 2019) for parameter selection, as shown in Table 4.

Result analysis

In this paper, the proposed potential assessment model based on time sequential simulation is built in MATLAB environment. Figure 7 shows the load curve adjustment effect of four units under three scenarios, and Figure 8 shows the load curve adjustment effect of the whole evaluation area. The proposed method was implemented in the YALMIP (Lofberg, 2004) optimization toolbox using MATLAB R2016a and solved by IBM ILOG CPLEX 12.6. The numerical experiments were performed on a computer with an Intel CORE CPU i5-1135G7 processor running at 2.40 GHz and 16 GB of RAM.

In Figure 7 and Figure 8, scenario 1 only considers the dispatching of energy storage device, and the load curve is smoothed by energy storage's releasing energy during peak periods and absorbing energy during valley periods. In scenario 2, only flexible load interaction response is considered, and the effect of peak shaving and valley filling is achieved through adjusting the transferable load and the reducible load. In Scenario 3, flexible load response and energy storage dispatch are jointly regulated. It is easy to see that scenario 3 has the most significant effect on load curve adjustment and improvement.

Table 5 shows the calculation results of the response potential evaluation indicators of the case. The results show that the regional load curve can be improved by rationally adjusting and controlling the user-side flexible loads and energy storage devices. The results of Table 5 show that the peak-shaving effect of 5%–6% and the valley-filling effect of less than 5% can be achieved only by load response participation, while both the peak-shaving effect and the valley-filling effect can be increased

TABLE 6 Benefit enhancing potential of each unit planning scheme.

Item	Unit A	Unit B	Unit C	Unit D	The whole area
Energy storage configuration cost (kRMB)	1640.2	2951.7	10858.0	1339.3	16789.2
Energy storage maintenance cost (kRMB)	0.204	3.424	1.246	0.115	4.989
Flexible load scheduling cost (kRMB)	4.090	1.709	6.931	1.356	14.086
Reduced capacity of distribution transformer (MVA)	4.596	6.167	19.282	3.396	31.14
Distribution transformer investment savings (kRMB)	6433.8	8633.5	26995.1	4754.9	43596.2
Investment in traditional planning schemes (kRMB)	27346.7	76580	82693.3	43446.7	230066.7
Total investment savings (kRMB)	4789.3	5676.7	16128.9	3414.1	26787.9
Total investment savings ratio (%)	23.5	11.3	32.6	10.9	18.9

to about 10% by adding energy storage dispatching. It can be seen that the addition of energy storage has a good effect on peak-shaving and valley-filling, especially valley-filling. The combined regulation of the overall flexible controllable load and energy storage can achieve the reducing rate of peak-valley difference by about 20%, and 5%–10% peak-shaving and valley-filling effect.

Figure 9 shows the daily optimal adjustment results of flexible load and energy storage device of each unit in the typical day under scenario 3. Through the application of a series of combination optimization methods, such as energy storage discharging the stored energy in the peak load period and charging in the valley load period, transferring the transferable load from the peak load period to the valley load period, and reducing the load properly in the peak load period, the effect of peak-shaving and valley-filling on the load curve is achieved.

Based on the above interactive response potential assessment results, we can roughly estimate the benefit-enhancing potential of the traditional planning scheme. According to the average load ratio of distribution transformer, that's 60% in this area, the configuration capacity of distribution transformers of this area can be reduced by about 31 MVA by adjusting various flexible resources in an ideal situation. And the investment cost can be saved by about 26.7 million RMB, which is 18.9% less than the investment cost of the traditional planning scheme. The benefit enhancing potential of each unit planning scheme is shown in Table 6.

Conclusion

This paper presents a response potential assessment method of user-side flexible resources of regional power distribution networks based on sequential simulation of optimal operation. First, a set of evaluation indicators, like variation rate of peak-valley difference and improvement rate of smoothness, are designed to characterize the improvement degree of the system load curve and the supporting potential to the power

grid planning and operation because of the flexible resources' participating in the interactive response with power grid. Then, a response potential assessment model of flexible resources is constructed based on sequential simulation of optimal operation considering the interaction between flexible resources and power grid, and the optimization software package is used to solve the model. In the end, the validity of the proposed method is verified by the analysis and evaluation of the flexible resource response potential in a certain area of North China.

The result shows that the user-side flexible resources participating in the interactive operation of the power grid can have a beneficial effect on the improvement of the system load curve, and the utilization potential is huge. In other words, flexible resources are a kind of balanced resources with good economy in the planning and operation of power network.

Therefore, we need to take the response potential assessment of flexible resources into account in the planning of future new type of distribution networks. In order to accurately evaluate the response potential of flexible resources, it is necessary to enhance the accuracy of load curve forecasting, the investigation and analysis of user load characteristics, and the accumulation of fine-grained historical data, so as to reasonably determine the interactive response parameters of flexible loads. At the same time, it is also necessary to introduce the methods of artificial intelligence, big data, etc., to carry out load forecasting, scenario construction, parameter acquisition and configuration, interactive strategy design of time series simulation, etc., so as to ensure the accuracy of the evaluation results. The above contents are also the focus of our further research to be conducted.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WL: Supervision, Conceptualization, Writing—review and editing. RL: Supervision, Conceptualization, Writing—review and editing. FL: Supervision, Conceptualization, Writing—review and editing. SF: Methodology, Software, Data curation, Writing—original draft. BY, ZLiu, ZLi, WZ, KK, and SL: Writing—review and editing.

Funding

This work is supported by Project of State Grid Shandong Electric Power Company (SGSDJY00GPJS2200234).

Acknowledgments

Thanks for the data support provided by the project team members from State Grid Shandong Electric Power Company. The authors would also like to thank the reviewers for their

valuable comments and suggestions to improve the quality of the paper.

Conflict of interest

WL, RL, BY, ZLu, ZLi, and WZ were employed by the company State Grid Shandong Electric Power Company.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 27 August 2022

ACCEPTED 16 September 2022

PUBLISHED 05 January 2023

CITATION

Fang J, Pei Z, Chen T, Peng Z, Kong S,
Chen J and Huang S (2023), Economic
benefit evaluation model of distributed
energy storage system considering
custom power services.
Front. Energy Res. 10:1029479.
doi: 10.3389/fenrg.2022.1029479

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Economic benefit evaluation model of distributed energy storage system considering custom power services

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This paper proposes an economic benefit evaluation model of distributed energy storage system considering multi-type custom power services. Firstly, based on the four-quadrant operation characteristics of the energy storage converter, the control methods and revenue models of distributed energy storage system to provide reactive power compensation, new energy consumption, peak-valley arbitrage and other customized power services are analyzed. Secondly, an economic benefit evaluation model of custom power services is formulated, considering the life cycle degradation cost, investment payback period, net present value, and internal return rate of energy storage. Finally, demonstrate the effectiveness and superior performance of the proposed methodology through comparative studies on the economic benefits and practical value. The influence of reserve capacity ratio of energy storage converter, additional price for power quality management, peak-valley price difference, battery cost and project cycle on the annual return and internal rate of return is revealed through the sensitivity analysis, which provides the decision-making reference for battery selection and capacity allocation of distributed energy storage system participating in various custom power services.

KEYWORDS

custom power services, power quality, peak-valley arbitrage, distributed energy storage system, economic benefit evaluation

1 Introduction

Generally, the custom power utilizes the advanced power electronics technology and control theory to provide power supply services that are higher than the national power supply standards for different users with specific demands and diverse requirements for power quality (Tao et al., 2014). Providing custom power services with diverse power quality can flexibly meet the demands of users and improve the economic operation of the power grid (Brenna et al., 2009; Liang et al., 2022). At present, the custom power services for power quality control including voltage sag, harmonics, and voltage deviation, are

mostly using the specific power quality control equipment, such as dynamic voltage restorer (Bae et al., 2010; Kumar and Tyagi, 2021), active power filter (Azhagesan et al., 2021), unified power quality regulator (Krishna et al., 2022), and static VAR compensator (Zaidan and Toos, 2021). The energy storage converter has the four-quadrant high-efficiency operation characteristics of bidirectional active and reactive power regulation. In addition to the conventional application scenarios such as renewable energy consumption (Murty and Kumar, 2020) and peak-valley arbitrage (Das et al., 2018), the energy storage converter has significant economic and technical advantages in power quality control including the voltage deviation and voltage sag as well (Alshehri and Khalid, 2019; Guo et al., 2019; LI et al., 2019; Liu et al., 2021; Akdogan and Ahmed, 2022). Brenna et al. (2009), LI et al. (2019), and Akdogan and Ahmed (2022) reviewed the research status and development trend of energy storage system for solving steady-state and dynamic power quality problems of power grid, and analyzed the feasibility of energy storage to solve the voltage deviation, harmonic and three-phase unbalance problems. Liu et al. (2021) proposed a day-ahead optimal scheduling model for integrated energy systems considering the potential economic benefits of energy storage, which can promote the active participation of energy storage in energy market scheduling for improving its profits. Guo et al. (2019) proposed a voltage coordinated control method for the high renewable penetrated distribution network based on the model predictive control, which can improve the voltage deviation of power grid through the four-quadrant regulation ability of active and reactive power of energy storage. Alshehri and Khalid (2019) proposed an optimal active and reactive power decoupling control method for the battery energy storage system to enhance the anti-disturbance ability of distribution network, while the improvement of power quality was not taken into account. Therefore, the energy storage system possesses unique technical advantages in solving the power quality problems, laying a solid theoretical foundation for providing various custom power services for energy storage.

In this paper, an economic benefit evaluation model of distributed energy storage system considering the custom power services is proposed to elevate the economic performance of distributed energy storage system on the commercial application and satisfying manifold custom power demands of different users. The main contributions of this paper are as follows:

- 1) A revenue model of distributed energy storage system is proposed to provide reactive power compensation, renewable energy consumption and peak-valley arbitrage services. An additional electricity pricing model of distributed energy storage system to provide reactive power compensation for users is formulated. The problems of long investment return period and insufficient utilization caused by the single profit mode of distributed energy storage system are solved.
- 2) A custom power services economic benefit evaluation model considering the life cycle cost, investment payback period, net present value and internal return rate of energy storage is formed. The influence of reserve capacity ratio of energy storage converter, additional price for power quality management and project cycle on annual return and internal rate of return is revealed by sensitivity analysis, which provides a decision-making basis for battery selection and capacity allocation of distributed energy storage system so as to participate in custom power services.

2 Revenue model of custom power services

A revenue model for distributed energy storage system to provide custom power services such as power quality management, peak-valley arbitrage, and renewable energy consumption is formulated in this section.

2.1 Power quality management

Since the energy storage converter has the fast power regulation characteristics of active and reactive power four-quadrant operation, making full use of its available reserve capacity to solve the power quality problem of distribution network has great economic benefits and regulation effects. The energy storage converter can implement the voltage deviation and reactive power compensation control of high renewable penetrated distribution network through the PQ control and droop control of active and reactive power coordination (Alshehri and Khalid, 2019). In addition, through the use of series-parallel energy system (LI et al., 2019), the series side can be similar to the dynamic voltage restorer (DVR) operation, and the parallel side can support reactive power adjustment to achieve the function of voltage deviation governance.

Revenues of energy storage for power quality management are from reactive power compensation service charge. Power quality management service charge is acquired by charging additional price for willingness to control according to unit power (Yang et al., 2006; Li et al., 2022; Lu et al., 2022), which is obtained through willingness price consultation with the users. Therefore, the annual revenue of energy storage participating in power quality management I_1 can be defined as follows,

$$I_1 = \sum_{i=1}^{N_{dva}} E_i \times e_{dva} \quad (1)$$

where I_1 is the service charge for reactive power compensation annually provided by the energy storage; E_i is the maximum

quality power for energy storage to provide reactive power compensation service for user i , valued by the reserve capacity of energy storage converter; e_{dva} is the additional price for reactive power compensation (Yang et al., 2006); N_{dva} is the amount of users of reactive power compensation services provided by the energy storage.

2.2 Distributed renewable energy consumption

With the steady growth of the proportion of distributed rooftop photovoltaic installation in the distribution network, the net load of the system will fluctuate rapidly in a short period of time due to the volatility and intermittency of photovoltaic output and anti-peak shaving characteristics of photovoltaic output and system load. At the same time, the renewable energy consumption ability of the distribution network is limited by the transmission capacity, resulting in renewable generation curtailment. Distributed energy storage system can separate power generation and consumption in time and space dimensions. It stores the surplus energy when the renewable energy generation exceeds the load, and releases the stored energy when the renewable energy generation is insufficient, improving the ability of renewable energy accommodation.

The distributed photovoltaic power releasing at the user side generally takes place when the sunlight is sufficient at noon. The energy storage system purchases surplus energy at on-grid price and obtains the corresponding income by selling at the peak price. Therefore, the annual revenue of energy storage participating in distributed renewable energy consumption I_2 is as follows,

$$I_2 = \sum_{i=1}^D \sum_{t=1}^T (\eta_{\text{cha}} \eta_{\text{dis}} P_{c,t} e_F - P_{c,t} e_S) \Delta t \quad (2)$$

where $P_{c,t}$ is the releasing power absorbed by energy storage at time t ; e_F is the peak price; e_S is the on-grid price, η_{cha} and η_{dis} are the charging and discharging efficiencies of the energy storage; D is the amount of annual operation days; T is the operation cycle, valued as 24 h; Δt is the operation time interval, valued as an hour.

2.3 Peak-valley arbitrage

The peak-valley arbitrage is the main profit mode of distributed energy storage system at the user side (Zhao et al., 2022). The peak-valley price ratio adopted in domestic and foreign time-of-use electricity price is mostly 3–6 times, and even reach 8–10 times in emergency cases. It is generally believed that when the peak-valley price difference transcends 0.7 CNY/kWh, the energy storage will have the peak-valley arbitrage profit

space (Li and Li, 2022). Usually, the energy storage is charged at night when the price is at valley stage, and discharges during the daytime when the power consumption is at peak, so as to achieve peak-valley arbitrage and save cost. Taking the charging/discharging strategy of the general industrial and commercial energy storage as an example, the annual revenue of energy storage participating in peak-valley arbitrage I_3 under the time-of-use price can be calculated as follows,

$$I_3 = \sum_{i=1}^D 2 \left(\eta_{\text{dis}} e_F - \frac{e_G}{\eta_{\text{cha}}} \right) \psi_{\text{DoD}} E_{\text{rat}} \quad (3)$$

where e_G is the valley price; E_{rat} is rated capacity of energy storage battery; ψ_{DoD} is the depth of discharge of energy storage battery, limited from 10% to 90% (Zhao et al., 2022).

3 Economic benefit evaluation

The economic benefit of distributed energy storage system to provide custom power services considering the cost of energy storage is analyzed and evaluated in this section.

3.1 Life cycle cost model of energy storage

The life cycle cost of energy storage is composed of initial investment cost, operation and maintenance cost, replacement cost, and recovery value. The initial investment cost contains the cost of energy storage battery C_{ESS} , the cost of energy storage converter C_{PCS} , and the cost of auxiliary facilities C_{BOP} at the initial stage of construction. The initial investment cost of energy storage C_{inv} is as follows,

$$C_{\text{inv}} = C_{\text{ESS}} + C_{\text{PCS}} + C_{\text{BOP}} = c_{\text{ESS}} E_{\text{rat}} + c_{\text{PCS}} P_{\text{rat}} + c_{\text{BOP}} E_{\text{rat}} \quad (4)$$

where c_{ESS} is the price per unit energy of energy storage battery; c_{PCS} is the unit power price of energy storage converter; c_{BOP} is the unit energy price of auxiliary facilities; P_{rat} and E_{rat} are the power and energy capacity of battery, respectively.

The annual operation and maintenance cost of energy storage C_{OAM} can be expressed as,

$$C_{\text{OAM}} = c_{\text{OAM}} P_{\text{rat}} \quad (5)$$

where c_{OAM} is the operation and maintenance cost per unit power.

The replacement cost refers to the cost that the energy storage equipment is required to be replaced during the operation of the project. In reality, since the energy storage converters and auxiliary facilities can always satisfy the rated operation life, the replacement cost here refers to the replacement cost of the battery C_{REP} , which can be expressed as follows,

$$C_{\text{REP}} = (1 - \beta)^{KM_L} C_{\text{ESS}} \quad (6)$$

where β is the annual decline proportion of battery cost; M_L is the battery life and K is the replacing times of energy storage in the project cycle.

Considering the time value of funds, the replacement cost in project cycle C'_{REP} can be reformulated as follows,

$$C'_{\text{REP}} = \sum_{j=1}^K \frac{(1-\beta)^{jM_L} C_{\text{ESS}}}{(1+\alpha)^{jM_L}} \quad (7)$$

where i is the discount rate; j is the j th replacement of energy storage.

The recovery value of energy storage I_{rec} refers to the remaining value of the battery, containing the installation cost C_{inv} and recovery coefficient γ of battery, as follows,

$$I_{\text{rec}} = \gamma C_{\text{inv}} \quad (8)$$

Considering the time value of funds, the recovery value of battery I'_{rec} in project cycle can be expressed as:

$$I'_{\text{rec}} = \gamma C_{\text{inv}} \sum_{\beta=1}^K \frac{1}{(1+\alpha)^{\beta M_L}} \quad (9)$$

In summary, the annual cost of energy storage C_{ALL} is as follows:

$$C_{\text{ALL}} = C_{\text{OAM}} + (C_{\text{inv}} + C'_{\text{REP}} - I'_{\text{rec}}) \frac{\alpha(1+\alpha)^N}{(1+\alpha)^N - 1} \quad (10)$$

where N is the project investment cycle.

3.2 Economic evaluation model

The economic benefit evaluation for energy storage is an important part to investigate the feasibility of the project, which offers an essential basis for the scientific decision-making in the early stage of project implementation and provides the technical support for distributed energy storage system project investment. This paper establishes a comprehensive economic benefit evaluation model of custom power services considering the net present value (NPV) of energy storage, investment recovery period and internal rate of return (IRR). Considering the average annual cost of energy storage and the annual revenue of custom power services, the economic benefit evaluation model can be formulated as follows:

$$F = I_1 + I_2 + I_3 - C_{\text{ALL}} \quad (11)$$

where F is the annual profit of energy storage. The value of F is greater than 0 indicating that the investment can be recovered during the operation of energy storage project.

NPV is one of the methods to evaluate the feasibility of investment scheme, which refers to the difference between the

discounted cash flow and the initial investment amount brought by project investment, as shown in Eq. 12,

$$\text{NPV} = \sum_{t=0}^N (I_{\text{in},t} - C_{\text{out},t}) (1+\alpha)^{-t} \quad (12)$$

where $I_{\text{in},t}$ is the net inflow in year t ; $C_{\text{out},t}$ is the net outflow in year t . The investment scheme is feasible/infeasible if the NPV is positive/negative.

Payback period refers to the time required to recover the total investment cost in the project life cycle. Considering the time value of funds, this paper selects the rate of dynamic investment return T_{rcv} for analysis, as follows,

$$\sum_{t=0}^{T_{\text{rcv}}} (I_{\text{in},t} - C_{\text{out},t}) (1+\alpha)^{-t} = 0 \quad (13)$$

IRR refers to the discount rate when the net cash flow accumulation is equal to zero during the project operation period, reflecting the rate of return that the project desires to achieve as shown in Eq. 14. The project is feasible/infeasible if the value of IRR is greater/less than the actual discount rate.

$$\sum_{t=0}^N (I_{\text{in},t} - C_{\text{out},t}) (1 + \text{IRR})^{-t} = 0 \quad (14)$$

4 Case analysis

4.1 Boundary condition

Adopting an energy storage system with an installed capacity of 500 kW/1,000 kWh built in 10 kV large industrial consumers in east China as a case, the energy storage operators and users share the economic benefits from renewable energy accommodation and peak-valley arbitrage according to the ratio of 8:2. On the basis of the local annual average electricity prices, the valley and peak prices are set to 0.2901 CNY/kWh and 1.0957 CNY/kWh, respectively. The renewable energy on-grid price is 0.4153 CNY/kWh, and the additional electricity charge for reactive power compensation is 0.003 CNY/kWh. The daily renewable energy consumption is 200 kWh and the annual operation time is 350 days. Assuming the length of project cycle is 10 years, the discount rate is set as 8% considering the battery replacement cost, labor cost, maintenance cost, and insurance expense.

Considering the peak-to-valley time division of the time-of-use price, the charge and discharge rates of the battery, the cycle life of the battery and the load characteristics of the consumers, the energy storage system in this paper adopt the strategy of double charge and discharge mode. In this operation mode, the charging periods of the energy storage power station are from 10.00 p.m. to 8.00 a.m. and 11.00 a.m. to 1.00 p.m., and the discharging periods are from 9.00 a.m. to 11.00 a.m. and

TABLE 1 Costs and technical performance parameters of four kinds of battery energy storage on the user side.

Battery type	Pb-C	NaS	LFP	V-redox
Energy-related cost (CNY/kWh)	1,000	1,300	1,500	2,500
Power-related cost (CNY/kW)	400	400	400	450
Auxiliary facility cost (CNY/kWh)	140	150	140	156
Fixed O&M (CNY/kWh-yr)	40	45	35	55
Charging efficiency (%)	89	80	95	75
Discharging efficiency (%)	89	80	95	75
Depth of discharge DOD (%)	80	80	80	80
Cycle life (cycles)	3,500–4,000	4,000–5,000	4,300–7,000	10,000
Capacity degradation (%/yr)	2	2	2	1

TABLE 2 Investment income analysis of energy storage system.

Battery type	Pb-C	NaS	LFP	V-redox
Rated power (kW)	500	500	500	500
Initial investment cost (CNY thousand)	1,340	1,650	1,840	2,880
Power quality management revenue (CNY thousand/yr)	40.7	40.7	40.7	40.7
Renewable energy consumption revenue (CNY thousand/yr)	19.5	20.6	26.3	10.2
Peak-valley arbitrage revenue (CNY thousand/yr)	221.6	225.9	260.2	155.3
NPV (CNY thousand)	94.5	−133.3	408.2	−1,136.3
IRR (%)	9.45%	6.06%	12.55%	−0.87%
Dynamic payback period (yr)	10.69	—	9.33	—

Bold values represent the optimal value in this comparison term for the four types of batteries.

3.00 p.m. to 5.00 p.m. Note that 1.00 p.m. to 3.00 p.m. in January, July, August, and December are set to the peak discharge periods. During the period from 10.00 p.m. to 8.00 a.m., the charging time is relatively rich and the energy storage can be charged slowly. During the period from 11.00 a.m. to 1.00 p.m., in order to provide energy for the upcoming peak and peak of electricity consumption, it is necessary to charge energy storage with high power and absorb renewable energy during this period. During the period from 9.00 a.m. to 11.00 a.m., in order to give full play to the energy storage capacity, the energy storage can be discharged at high power. During the period from 1.00 p.m. to 5.00 p.m., the dischargeable response time is long, and thus the discharge power can be dynamically and flexibly adjusted.

Lead-carbon battery, sodium-sulfur battery, lithium iron battery and vanadium redox battery are selected as typical distributed energy storage system for research. The specific costs and technical performance parameters are shown in Table 1.

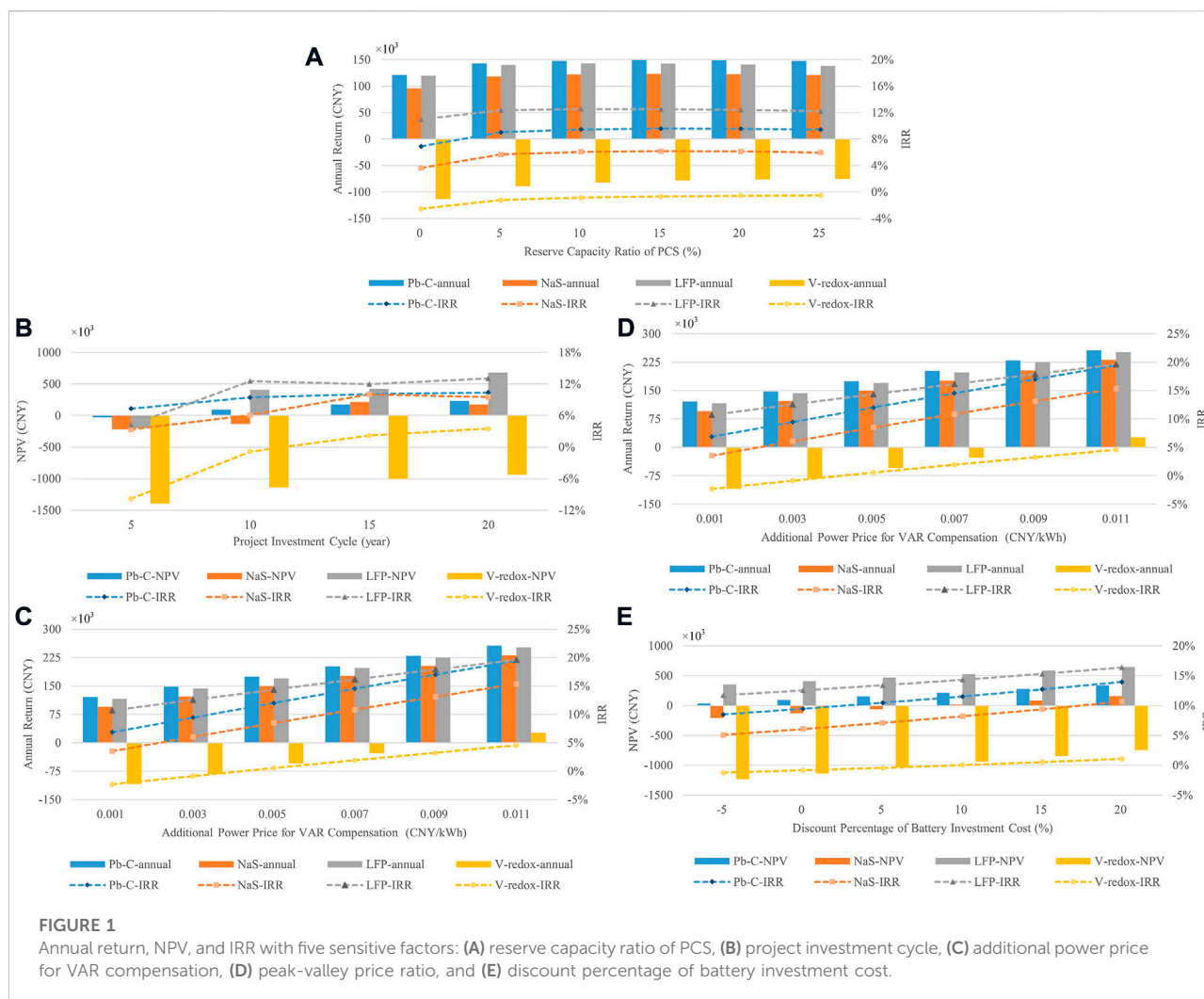
4.2 Comparative analysis

According to the model and parameter settings in Section 4.1, the economic benefits of four battery energy storage systems are

calculated and compared. The total investment economic benefits are shown in Table 2.

The calculation results show that the initial investment cost of the lead-carbon battery is lower than that of the other three batteries, and it has the advantage of construction cost. However, its maximum charge and discharge time and battery life are low, and a battery replacement is needed in the project cycle. It can also be observed that the economic performance of lead-carbon battery is worse than that of lithium iron phosphate battery considering the cost of battery replacement. The NPV, IRR and investment payback period of lithium iron battery in the 10-year project cycle are 408.2 thousand CNY, 12.55% and 9.33 years, respectively. The single profit of lithium iron battery in various custom power scenarios is higher than that of the other three batteries due to the characteristics of long life, high safety and easy maintenance. Therefore, when the project cycle is 10 years long, it is of more reference value and engineering application value to use lithium iron battery as the energy storage to provide custom power services considering the economy and battery technical characteristics.

It can be found from Table 2 that the majority of the revenue from energy storage for custom power services comes from the peak-valley price differential arbitrage. The calculation results show that the power quality management, renewable energy photovoltaic consumption and peak-valley arbitrage account



for 14.44%, 6.93% and 78.63%, respectively. In the above cases, the proportion of energy storage capacity required for power quality management is only 10%, but the benefits are considerable, indicating that energy storage provides power quality management services with good commercial prospects. Therefore, through the economic calculation of energy storage application in custom power services, it provides a new development direction for energy storage to explore new profit models and improve the income level of energy storage.

4.3 Sensitivity analysis

Figure 1A shows the relationship between the annual return and IRR of the four battery energy storages with the different proportion of reserve capacities. When other parameters remain unchanged, the sensitivity analysis is carried out by setting reserve capacity ratios of 0%, 5%, 10%, 15%, 20%, and 25%,

respectively. With the increase of reserve capacity, the annual return and IRR of the four batteries show a trend of increase at the beginning and then decrease. When there is a certain reactive reserve capacity, the energy storage can provide reactive compensation service to obtain benefits. However, when the proportion of reserve capacity continues to increase, the increase of reactive power compensation income is not obvious and the active output of converter is limited, which reduces the income of peak-valley arbitrage and thus the overall income is decreased. Among them, the annual return of lead-carbon battery increases from 121.24 thousand CNY to 149.19 thousand CNY, reaching the maximum when the proportion of reserve capacity is 15%, and finally decreases to 147.61 thousand CNY. The IRR rises from 6.91% to 9.59%, and reaches its maximum at a reserve capacity ratio of 15% and finally falls to 9.44%.

Figure 1B is the relationship between NPV and IRR of four kinds of battery energy storage with project cycle. In the case of

constant parameters, the project cycles are set as 5, 10, 15, and 20 years for sensitivity analysis. Four kinds of battery energy storage NPV and IRR show an increasing trend with the increase of project cycle. When the project cycle is 5 years, the lead-carbon battery has better economic performance than the sodium sulfur battery, lithium iron battery and vanadium redox battery because of its low cost and no replacement cost. When the project cycle is more than 10 years, the IRR of lithium iron battery exceeds 10% due to its good charge and discharge efficiency and cycle life, which is more than other types of batteries. Therefore, the lead-carbon battery can be used as the energy storage system when the project cycle is less than 5 years. Moreover, when the project cycle is more than 10 years, the use of lithium iron battery with the characteristics of safe and easy maintenance as the energy storage is better.

Figure 1C shows the relationship between the annual return and IRR of the four battery energy storages and the additional electricity price of power quality. In the case of constant parameters, the sensitivity analysis was carried out by setting the additional power charges of 0.001, 0.003, 0.005, 0.007, 0.009, and 0.011 CNY/kWh, respectively. The annual profit and IRR of four kinds of battery energy storage show a linear growth trend with the increase of power quality additional charge. Among them, the lead-carbon battery energy storage in the process of increasing the additional power cost of power quality from 0.001 CNY/kWh to 0.011 CNY/kWh, the annual income increases from 120.66 to 256.27 thousand CNY, and the IRR increases from 6.85% to 19.43%. Therefore, the increase of the additional electricity charge has a positive effect on the growth of energy storage income.

Figure 1D shows the relationship between the annual return and IRR of the four battery energy storages with the peak-valley price difference. At present, the peak-valley arbitrage of energy storage is mostly the peak-valley price arbitrage, and the peak price is about four times that of the valley price. In the case of constant parameters, the peak-valley price ratios are set to be 2, 4, 6, and 8 times for sensitivity analysis. With the increase of peak-valley price difference, the annual return and IRR of the four types of battery energy storages increase linearly. Among them, the peak-valley price difference of the lead-carbon battery energy storage increases from 2 times to 8 times, and its annual return and IRR rise from −54.13 to 627.65 thousand CNY and −11.40%–50.93%, respectively, indicating that the peak-valley price difference has a great impact on the energy storage income.

Figure 1E shows the relationship between the NPV and IRR of the four battery energy storages and the decrease of battery cost. In the case of constant parameters, the sensitivity analysis was carried out by setting the battery cost reduction percentages of −5%, 0%, 5%, 10%, 15%, and 20%, respectively. The investment returns of four kinds of battery energy storage increase linearly with the decrease of battery cost. When the battery cost decreases from −5% to 20%, the cumulative NPV of lead-carbon battery energy storage increases from 34.46 to

334.70 thousand CNY, and the IRR increases from 8.51% to 13.95%.

5 Conclusion

In this paper, the economic benefit evaluation model of distributed energy storage system considering custom power services is established. Through the assessment and sensitivity analysis of multi-type distributed energy storage system including the lead-carbon battery, sodium sulfur battery, lithium iron battery and vanadium redox battery, the main conclusions are summarized as follows:

- (1) The energy storage converter has the fast power regulation characteristics of active/reactive four-quadrant operation. Participation in reactive power compensation, renewable energy consumption and peak-valley arbitrage can bring great economic benefits to the energy storage project, which provides a novel idea for the transformation of the business model of distributed energy storage system from the price difference-based to comprehensive profit, and is conducive to promoting the commercial promotion and diversified development of distributed energy storage system on the user side.
- (2) The economy of distributed energy storage system participating in the custom power services increases at the beginning and then decreases with the increase of the reserve capacities. When there is a certain reactive reserve capacity, the energy storage can benefit by providing reactive power compensation service. With the increase of the reserve capacity, the maximum active power output of energy storage converter decreases, and the benefits of peak-valley arbitrage and renewable energy consumption decrease gradually. However, the increase of reactive power compensation benefits is not obvious, which reduces the overall economy of energy storage. Through sensitivity analysis, it is found that the economic performance is optimal when the proportion of converter reserve capacity is 15%.
- (3) The economic benefits of energy storage systems are greatly affected by the length of project cycle. When the project cycle is shorter than 5 years, lead-carbon battery has better economic performance than sodium sulfur battery, lithium iron battery and vanadium redox battery because of its cost advantage. When the project cycle is longer than 10 years, lithium iron phosphate battery performs better in economic benefits due to its charge-discharge efficiency and cycle life advantages. With the development of energy storage material technology in the future, the price cost of lithium battery will gradually decrease, and its cost performance will show obvious economic advantages and market demand.

(4) Energy storage income is greatly affected by market mechanism. The energy storage economy increases linearly with the increase of peak-valley price difference and high-quality electricity additional price. Besides, the change of market mechanisms such as peak-valley price pricing mechanism will affect the energy storage benefits. Under the market-oriented electricity sale mode, the price fluctuates up and down according to the market supply and demand, providing a wide profit space for the peak-valley arbitrage of energy storage. The establishment of auxiliary service market can provide a broad space for the development of energy storage to offer power quality services. The increase of users' demands for power quality will increase the service cost of reactive power compensation and provide profitable space for the power quality management of energy storage.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

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Author contributions

Writing the original draft and editing, JF; Conceptualization, ZGP and TC; Formal analysis, ZHP and SK; Visualization and contributed to the discussion of the topic, JC and SH.

Conflict of interest

Authors JF, ZGP, TC, SK and JC were employed by Shaoxing Power Supply Company State Grid Zhejiang Electric Power Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 14 June 2022
ACCEPTED 31 August 2022
PUBLISHED 05 January 2023

CITATION
Fei Z, Longjiang X, Jingliang Z, Ding C,
Jinghui F and Jun W (2023), A novel
investment strategy for renewable-
dominated power distribution networks.
Front. Energy Res. 10:968944.
doi: 10.3389/fenrg.2022.968944

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A novel investment strategy for renewable-dominated power distribution networks

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Aiming at the problem of insufficient adaptability to the new elements of the new power system in the current distribution network investment method, this paper innovatively proposes a distribution network investment method based on the new power system. By constructing a source-grid-load-storage-side investment calculation model, the investment in the new power system can be accurately calculated. First, the distributed power investment is calculated from the two aspects of new construction and renovation. Secondly, construct the grid investment demand and grid investment capacity measurement model, and obtain the grid side investment model by weighted summation. Then, a model for calculating the scale of investment that can be saved due to demand-side response is constructed, and the cost of demand response is subtracted to obtain a model for calculating the scale of investment that can be saved on the load side. Finally, the energy storage side investment calculation model is constructed from the power supply side, grid side, user-side energy storage investment, and energy storage investment benefit. The research results are applied to the empirical area, and scientific guidance is provided to realize the precise investment in the area.

KEYWORDS

new power system, distribution network investment, source network load-storage, calculation model, precise investment

1 Introduction

Building a new type of power system is an all-round change, a very challenging and pioneering strategic project (Sánchez et al., 2022). From the perspective of power grid investment, the investment structure and focus will undergo major changes (He et al., 2022). Power grid enterprises should actively implement the reform of management methods (Zhu et al., 2022), change investment concepts and thinking in a timely manner, accurately grasp the focus and direction of investment, optimize investment strategies (Zhang et al., 2022), and provide sufficient and accurate investment support for the construction of new power systems.

At present, experts and scholars have conducted much research on distribution network investment methods. Reference (Ren et al., 2019) estimates the size of the

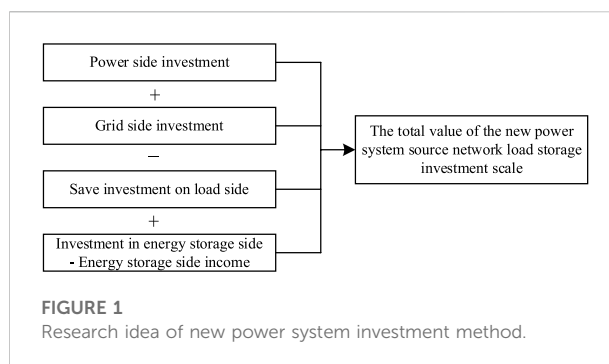
distribution network based on the current situation and load growth of the distribution network, and proposes a model strategy for distribution network investment allocation in combination with regional development needs, economic and social benefits of investment. Reference (Zheng et al., 2021) establishes an improved comprehensive evaluation method and evaluation model of distribution network investment benefit based on the individual evaluation results of investment benefit of distribution network reconstruction project, combined with information entropy and fuzzy analysis method. Reference (Wu et al., 2019) starts from technology, benefit, and project maturity, and builds an index system for investment ranking and evaluation of power grid planning projects under the new power reform environment. The precise investment decision of the distribution network in the above literature is mainly aimed at the traditional power system and has insufficient adaptability to the new elements of the new power system.

In order to implement the dual carbon goal, the state proposes to build a new power system with new energy as the main body. Compared with the traditional power system, its core feature is that new energy occupies a dominant position. In the future, wind power, photovoltaics, and energy storage will show explosive growth. Reference (Elkadeem et al., 2019) proposes an optimal investment model for a distribution network with renewable energy that considers efficiency, benefit, and carbon emission reduction. Based on the research of regional multi-energy system model, reference (Nazir et al., 2021) proposes a regional renewable energy generation capacity planning and investment benefit optimization model based on different dispatch time scales. Reference (Gao and Zhao, 2018) used system dynamics and evolutionary game methods to study the willingness of all parties to photovoltaic projects under the contract energy management model. Although the above references all add new elements related to renewable energy and storage, they do not fully consider the impact of new elements on the investment and construction of the new power system on the four sides of the source, network, load and storage.

In order to adapt to the new elements of the new power system, this paper proposes a distribution network investment method based on the new power system. By constructing the four-side investment model of source, network, load, and storage, and predicting and analyzing the investment data of each side, the asset investment strategy of power grid enterprises can be adjusted. It is of great significance to realize precise investment and improve market competitiveness.

2 Research ideas for new power system investment methods

The general idea of research on new power system investment methods is shown in Figure 1.



The formula for calculating the total investment scale of the source, grid, load, and storage side of the new power system is shown in Eq. 1:

$$T = C + G - L + (W - I) \quad (1)$$

In the formula, C is the power supply-side investment. G is the grid side investment. L is the investment on the energy storage side. W is the energy storage side investment. I is the energy storage side investment, respectively.

Investment on the power supply side: In response to the need of accelerating the construction of a clean, low-carbon, safe and efficient modern energy system, taking clean development as the direction, and investing in optimizing the power supply structure on the basis of ensuring energy security.

Grid-side investment: In order to accelerate the transformation of the distribution network from a single power supply to an intelligent and interactive energy Internet, realize a first-class modern distribution network with high reliability, good interaction, economic efficiency, and reasonably and effectively meet the demand for load growth and safe and reliable power saving on the load side: the investment in the construction of high, medium, and low voltage distribution networks that can be saved due to interruptible load response, etc. Minus the cost of demand response.

Energy storage side investment: the initial cost investment of energy storage on the power supply side, the grid side, and the user side, and the operation cost investment minus the energy storage subsidy.

Energy storage side income: The income from increasing on-grid electricity, reducing the deviation of power generation plant, and providing auxiliary services is the energy storage income on the power supply side; the income such as delaying the investment in grid construction is the energy storage income on the grid side; the income such as peak-valley arbitrage is the energy storage income on the user side.

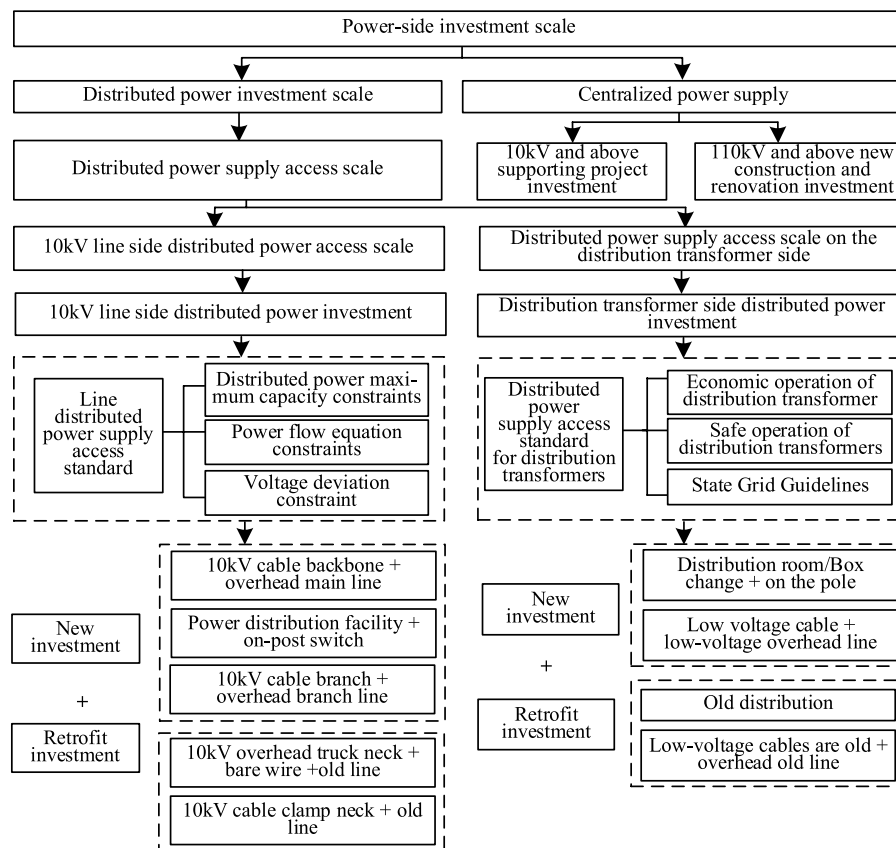


FIGURE 2
Flow chart of investment scale calculation of power supply side in future years.

3 Research on calculation model of new power system power supply side investment

Figure 2 shows the calculation process of the investment scale of the power supply side in the future.

The total investment scale of the power supply side is the sum of the investment in the centralized power supply and the investment in the distributed power supply. This paper mainly studies the calculation method of the investment scale of the distributed power supply (Abdelkader et al., 2018). The calculation formula is shown in Eqs. 2–3:

$$C = C_{fb} + C_{jz} \quad (2)$$

$$C_{fb} = C_1 + C_2 + C_3 + C_4 \quad (3)$$

In the formula, C_{fb} is the total investment in distributed power. C_{jz} the investment in centralized power. C_1 and C_2 are the investment in the construction and reconstruction of 10 kV lines to meet the needs of distributed power supply access. C_3 and

C_4 are the construction and reconstruction of distribution transformers, respectively.

3.1 10 kV line-side distributed power investment

Considering that the tie line satisfies the N-1 check and the maximum load rate of the single radiation line does not exceed 70%, the maximum access capacity of the single-circuit 10 kV line distributed power supply is 6 MW.

1) Investment in new 10 kV lines and power distribution facilities

The calculation formula is shown in Eq. 4:

$$C_1 = \frac{a(S_{LDGZ} - \lambda S_{LDGZ})}{6} (r_{dz} P_{dzz} + y_1 P_{zpd} + y_2 r_{dfz} P_{dfz}) + \frac{b(S_{LDGZ} - \lambda S_{LDGZ})}{6} (r_{jz} P_{jzx} + y_3 P_{zzs} + y_4 r_{jffz} P_{jffz}) \quad (4)$$

In the formula, S_{LDGZ} is the total installed capacity of the distributed power supply on the 10 kV line side; a and b are the proportions of cables and overhead lines in newly built lines respectively; λ is the current 10 kV line consumption proportion of distributed power. r_{dz} and P_{dzz} are the length and cost of the newly-built single-circuit 10 kV cable trunk line respectively; y_1 and P_{zpd} are the number and cost of the newly-built power distribution facilities (ring network room, branch-box) of the single-circuit cable line respectively; y_2 is a single distribution Number of newly-built cable branch lines for electrical facilities; r_{dfz} and P_{dfz} are the unit length and cost of 10 kV cable branch lines; r_{jz} and P_{jzx} are the length and cost of newly-built single-circuit 10 kV overhead main lines respectively; y_3 and P_{zss} are newly-built pole switches for single-circuit overhead lines quantity and cost; y_4 , r_{jz} , P_{jz} are the number, length, and cost of newly-built branch lines of a single-circuit 10 kV overhead line, respectively.

2) Investment in transforming 10 kV lines

The calculation formula is shown in Eq. 5:

$$C_2 = (r_{zjk} + r_{zjlj} + r_{zld})P_{jzx} + (r_{zdk} + r_{zdlj})P_{dzz} \quad (5)$$

In the formula, r_{zjk} , r_{zjlj} , r_{zld} are the current 10 kV overhead clamp neck, old and bare conductor line length respectively; r_{zdk} and r_{zdlj} are the current 10 kV cable clamp neck and old-line length, respectively.

3.2 Distribution and transformation side distributed power investment

After calculation, the maximum distributed power access capacity S_{PDG} of a single distribution transformer is 0.8 times the capacity of the distribution transformer.

1) Investment in new distribution transformers

The calculation formula is shown in Eq. 6:

$$C_3 = \frac{pg(S_{PDGZ} - \rho S_{PDGZ})}{0.5 \times 0.6S_{xb}} (P_{xb} + z_1 r_{dd} P_{ddx}) + \frac{qg(S_{PDGZ} - \rho S_{PDGZ})}{0.5 \times 0.6S_p} (P_p + z_2 r_{dj} P_{dix}) \quad (6)$$

In the formula, S_{PDGZ} is the total installed capacity of 10 kV distribution transformer side distributed power; p is the proportion of power distribution room/box substation in newly built low-voltage equipment; g is the proportion of the current number of public transformers to the total number of distribution transformers; ρ is the proportion of distributed power supply consumed by the current distribution transformer; S_{xb} is the capacity of a single power distribution

room/box substation. P_{xb} is the cost of a single power distribution room/box substation; z_1 , r_{dd} and P_{ddx} are the single power distribution room/box substation, respectively the number, length, and cost of newly built low-voltage cable lines; q is the proportion of pole-mounted transformers in newly built low-voltage equipment. S_p and P_p are the capacity and investment of a single distribution transformer respectively; z_2 , r_{dj} and P_{dix} are the newly built low-voltage overhead lines of a single distribution transformer number, length, and cost.

2) Investment in the transformation of distribution transformers

The calculation formula is shown in Eq. 7:

$$C_4 = t_{lj} P_p + r_{dij} P_{dix} + r_{ddl} P_{ddx} \quad (7)$$

In the formula, t_{lj} is the number of old distribution transformers; r_{dij} and r_{ddl} are the lengths of the old lines of low-voltage overhead and cables, respectively.

4 Research on calculation model of grid side investment in new power system

Figure 3 shows the calculation process of the investment scale on the grid side in the future.

The calculation formula for the investment scale on the grid side is shown in Eq. 8:

$$G = \mu_g (\alpha G_{xq} + \beta G_{nl}) \quad (8)$$

In the formula, G_{xq} is the power grid investment demand. μ_g is the correction factor. G_{nl} is the power grid investment capacity. α and β are the investment demand of the power grid and the proportion of investment capacity, respectively, which can be determined by the analytic hierarchy process.

4.1 Grid investment demand estimation

The idea of investment demand estimation is shown in Figure 4.

1) Influencing factor system of power grid investment demand

The indicator system is shown in Figure 5.

4.2 Correlation analysis

The selection of key impact indicators is carried out through correlation analysis (Gao et al., 2022). Correlation analysis refers

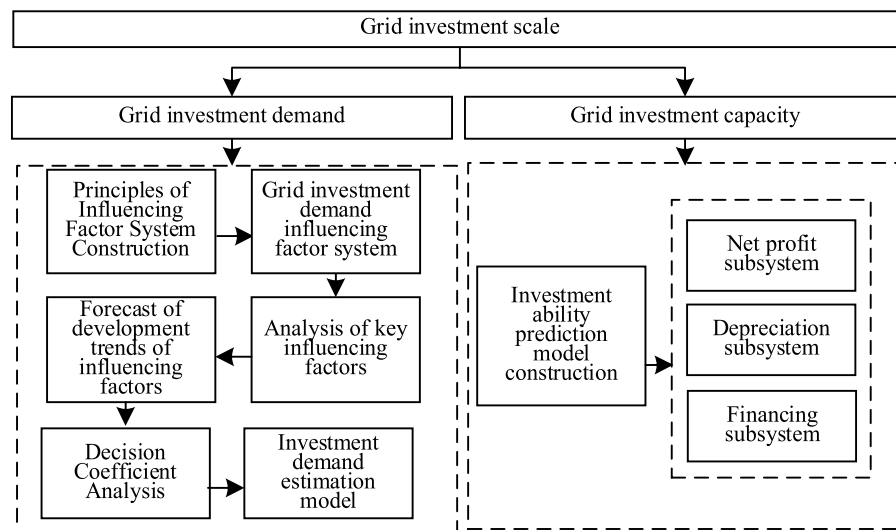


FIGURE 3
Calculation flow chart of investment scale of grid side in future years.

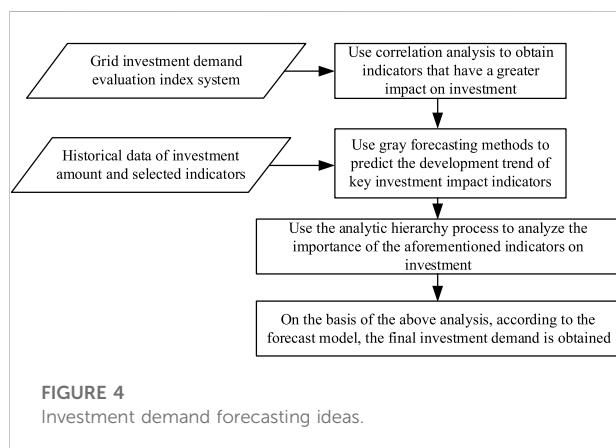


FIGURE 4
Investment demand forecasting ideas.

to the analysis of two or more related variable elements to measure the closeness of the correlation between the two variable factors.

The calculation of the correlation coefficient is shown in Eq. 9:

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}} = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2} \sqrt{\sum (y - \bar{y})^2}} \quad (9)$$

In the formula, r is the correlation coefficient, n is the number of data items; $\bar{x}$ is the arithmetic mean of the independent variable series; $\bar{y}$ is the arithmetic mean of the dependent variable series y .

From the correlation analysis, the key impact indicators are GDP, the number of power supply households, electricity sales, total profit, and the highest load of the whole society.

3) Forecast of the development trend of influencing factors based on gray forecast

The amount of data required for gray prediction is small. When processing the data, it does not seek the probability distribution and statistical law of the data but uses the “gray generation method” to seek a new sequence with weakened randomness and strengthened regularity. The GM (1, 1) model is used for the prediction of the development trend of the influencing factors.

The initial year index value is recorded as $X^{(0)}$, and the initial number column is $X^{(0)} = (X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n))$. Reference (Luo et al., 2021) builds a model by the cumulative generation of the grey generation method, then the model is:

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{u}{a} \right] e^{-ak} + \frac{u}{a}, k = 0, 1, \dots, n-1 \quad (10)$$

By reducing the above formula, the gray prediction model of the original sequence can be obtained as:

$$\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(k-1), k = 2, 3, \dots, n \quad (11)$$

4) Decision coefficient analysis based on AHP (Wang et al., 2021)

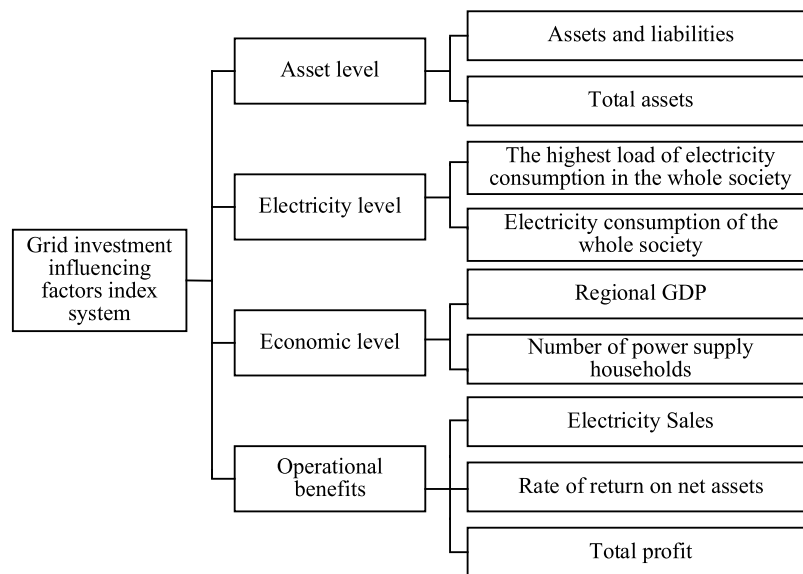


FIGURE 5
Investment scale forecast influencing factors.

The analytic hierarchy process is used to analyze and predict the decision coefficient of key impact indicators. The calculation steps are as follows:

4.3 Establish a judgment matrix

Generally, the judgment matrix is established by the reciprocal 1–9 scale scaling method. Assuming that the judgment matrix is: $A = \begin{bmatrix} a_{11} & \dots & a_{1m} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mm} \end{bmatrix}$, then the element a_{ij} of the judgment matrix A corresponds to the relative importance of the two elements a_i and a_j in the hierarchy.

4.4 Calculation method of decision coefficient

Assuming that the judgment moment is $A = \begin{bmatrix} a_{11} & \dots & a_{1m} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mm} \end{bmatrix}$, firstly multiply each element by row and raise it to the power m , that is, to obtain the geometric mean of the elements in each row, as shown in Eq. 12:

$$b_i = \left(\prod_{j=1}^m a_{ij} \right)^{1/m} \quad (i = 1, 2, \dots, m) \quad (12)$$

TABLE 1 Average stochastic consistency indicator parameters.

m	1	2	3	4	5	6	7	8	9
R.I.	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

By normalizing $b_i (i = 1, 2, \dots, m)$ again, the decision coefficient of each element of the criterion layer or the scheme layer can be obtained, as shown in Eq. 13:

$$\omega_j = \frac{b_j}{\sum_{k=1}^m b_k} \quad (j = 1, 2, \dots, m) \quad (13)$$

4.5 Consistency check of judgment matrix

The rationality of the decision coefficient can be verified by the consistency of the judgment matrix. If the judgment matrix can pass the consistency check, it means that the decision coefficient is reasonable; otherwise, the decision coefficient is unreasonable.

Calculate the maximum eigenvalue $\lambda_{\max}$ of the judgment matrix, as shown in Eq. 14:

$$\lambda_{\max} = \frac{1}{m} \sum_{j=1}^m \frac{\sum_{i=1}^m a_{ij} \omega_j}{\omega_j} \quad (14)$$

To calculate the consistency index $C.I.$, the formula is shown in Eq. 15:

$$C.I. = \frac{\lambda_{\max} - m}{m - 1} \quad (15)$$

Define the mean consistency metric $R.I.$.

4) Calculate the random consistency ratio $C.R.$, the formula is shown in Eq. 16:

$$C.R. = \frac{C.I.}{R.I.} \quad (16)$$

The average random consistency index $R.I.$ can be found from the Table 1 according to the matrix order m .

4.6 Check the consistency of the judgment matrix, as follows

When $C.R. = \frac{C.I.}{R.I.} < 0.1$, it is considered that the judgment matrix has acceptable inconsistency, otherwise, it is considered that the initially established judgment matrix is unsatisfactory and needs to be re-assigned and carefully revised until the consistency check is passed.

5) Grid investment demand estimation

Construct an investment demand estimation model as shown in Eq. 17:

$$G_{xq} = \sum_{i=1}^n u_i \times \left[\frac{y_i(k+1) - y_i(k)}{y_i(k) - y_i(k-1)} \right] \times x(k) \quad (17)$$

In the formula, G_{xq} is the investment demand of the regional distribution network in the next year; u_i is the factor's decision-making coefficient; $y_i(k+1)$ is the value of the next year's factor; $y_i(k)$ is the value of the current year's factor; $y_i(k-1)$ is the value of the previous year's factor; $x(k)$ is the amount of grid input for this year.

4.7 Grid investment capacity calculation model

Figure 6 shows the calculation idea of investment capacity.

The power grid investment capacity prediction model (Yi et al., 2021) can be divided into profit subsystem, depreciation subsystem, and financing subsystem.

The investment ability prediction formula is shown in Eq. 18:

$$G_{nl} = N_p - T_p + D + F \quad (18)$$

In the formula, G_{nl} is the investment capacity of the power grid company. N_p is the net profit of the power grid company. T_p is the profit turned over by the power grid company. D is the depreciation amount. F is the financing amount.

1) The net profit subsystem is shown in Eq. 19:

$$N_p = S_D + TZ_p + Y_p + Q_p - CB_Z - S_p \quad (19)$$

In the formula, S_D is the income from electricity sales. TZ_p is the investment income. Y_p is the income from the outside business. Q_p is the income from other businesses. CB_Z is the total cost and expense. S_p is the income tax.

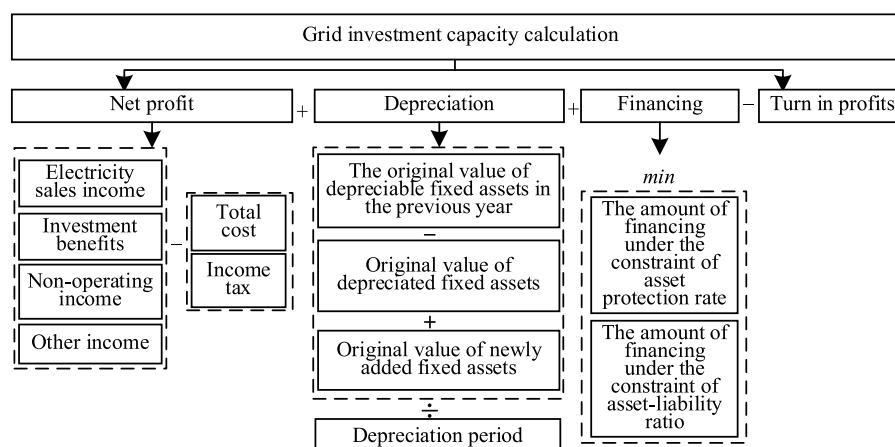


FIGURE 6
Investment capacity forecast flow chart.

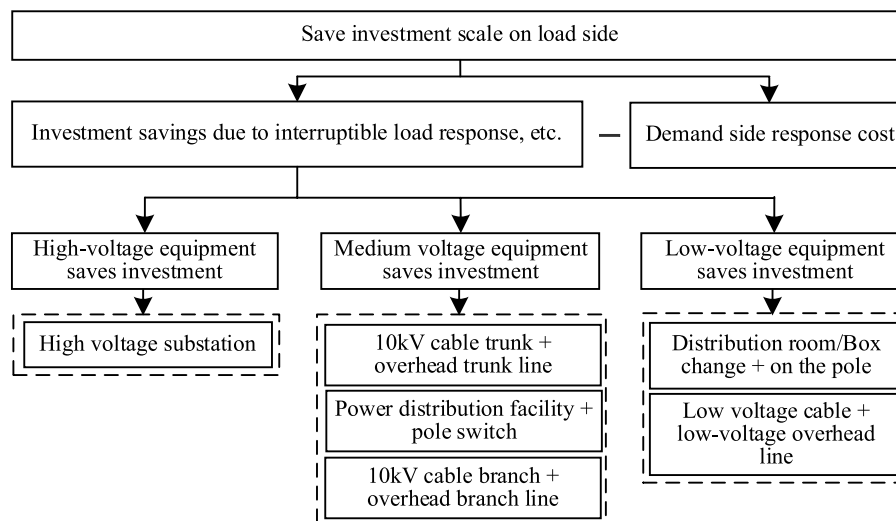


FIGURE 7
Flow chart of the scale of investment savings on the load side in the coming years.

2) The depreciation subsystem is shown in Eq. 20:

$$D = (D_{ZCL} - D_{ZCT} + \Delta D_{ZC})/N \quad (20)$$

In the formula, N is the depreciation period. D_{ZCL} is the original value of depreciable fixed assets in the previous year. D_{ZCT} is the original value of depreciable fixed assets. ΔD_{ZC} is the original value of newly added fixed assets.

3) The financing subsystem is shown in Eqs. 21–23:

$$F = \min(F_{BZ}, F_{FZ}) \quad (21)$$

$$F_{BZ} = (N_p - T_p + D) \times \varepsilon \times (1 - \lambda_{BZ})/\lambda_{BZ} \quad (22)$$

$$F_{FZ} = \frac{\lambda_{FZ}(F_{ZCL} + N_p - T_p - F_{HK}) - F_{FZL} + F_{HK}}{1 - \lambda_{FZ}} \quad (23)$$

In the formula, F_{BZ} and F_{FZ} are respectively the financing amount under the constraints of capital security rate and debt ratio. ε is the cash flow coefficient; λ_{BZ} is the capital security rate. λ_{FZ} is the asset-liability ratio. F_{HK} is the repayment amount. F_{ZCL} and F_{FZL} are the assets and assets total liabilities.

5 Research on the calculation model of new power system load-side saving investment

Figure 7 shows the calculation process of the scale of investment savings on the load side in the coming years.

The formula for calculating the scale of saving investment on the load side is shown in Eqs. 24–25:

$$L = L_{xq} - L_{cb} \quad (24)$$

$$L_{xq} = L_{gxq} + L_{zxq} + L_{dxq} \quad (25)$$

In the formula, L_{xq} is the saving investment on the demand side. L_{cb} is the cost of demand response. L_{gxq} is the high-voltage substation to save investment. L_{zxq} is the saving of investment in medium voltage equipment. L_{dxq} is for low-voltage equipment to save investment.

The cost of demand-side response (Yang et al., 2021) is calculated according to the regional demand response subsidy price scheme.

6 Research on investment calculation model of energy storage side of new power system

6.1 Energy storage side investment calculation model

Figure 8 shows the calculation process of the investment scale of the energy storage side in the future.

The total investment cost of the energy storage system is shown in Eqs. 26–28:

$$W = W_1 + W_2 \quad (26)$$

$$W_1 = W_{ps}P_{EN} + W_{es}E_N \quad (27)$$

$$W_2 = W_{omp}P_{EN} + W_{ome}E_N \quad (28)$$

In the formula, W_1 is the initial energy storage system cost. W_2 is the operation and maintenance cost. W_{ps} is the

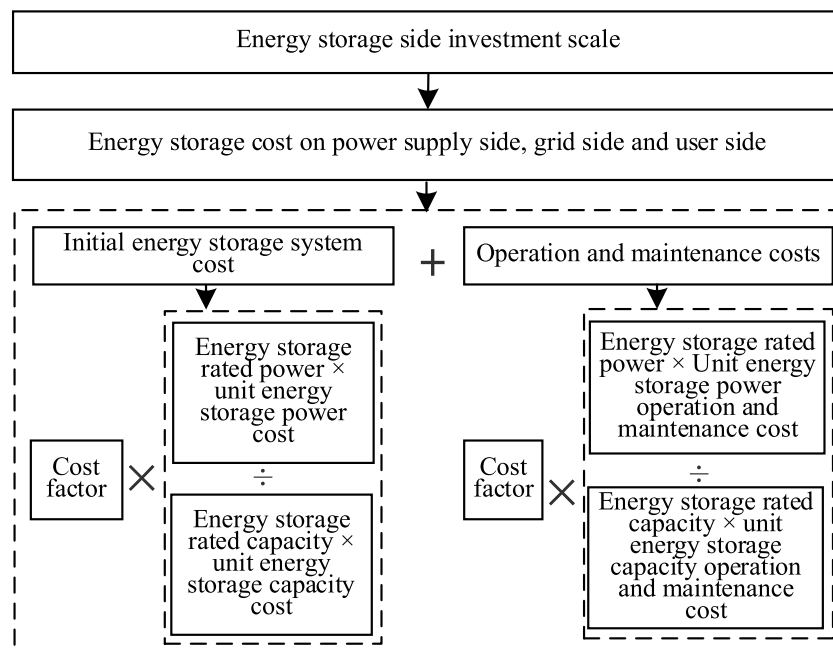


FIGURE 8
Calculation flow chart of investment scale of energy storage side in the future.

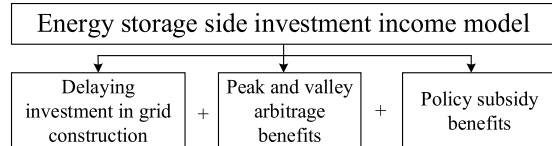


FIGURE 9
Flow chart of future annual investment income calculation of energy storage side.

unit energy storage power cost. P_{EN} is the energy storage rated power. W_{es} is the unit energy storage capacity cost. E_N is the rated capacity of energy storage. W_{omp} is the operation and maintenance cost of unit energy storage power. W_{ome} is the operation and maintenance cost of unit energy storage capacity

6.2 Energy storage side investment income model

Figure 9 shows the calculation process of the investment income of the energy storage side in the future.

The future annual investment income of the energy storage side is shown in Eq. 29:

$$I = I_{dw} + I_{tl} + I_{bt} \quad (29)$$

1) Delaying investment in grid construction

The economic benefits of reducing investment in grid expansion and reconstruction by installing energy storage can avoid fixed capacity costs, which can be determined according to the average cost of substations, transformers, transmission lines, and their supporting equipment that are less or delayed in construction, as shown in Eq. 30:

$$I_{dw} = A_t \varphi \eta P_{\max} \quad (30)$$

In the formula: I_{dw} is the investment in grid construction that can be delayed. A_t unit power cost of distribution network. φ is the fixed asset depreciation rate of power distribution equipment. η is the charge-discharge efficiency. $P_{\max}$ is the rated power of the energy storage.

2) Peak and valley arbitrage income

Under the premise of charging and discharging twice a day, the main benefits of user-side energy storage projects are the peak-valley price difference and the peak-to-parity price difference arbitrage.

Assuming two charges and two discharges per day, the peak electricity price under special circumstances is not considered,

TABLE 2 Comparison of calculation results of two grid investment calculation methods.

Year	Actual grid investment scale (ten thousand dollars)	Calculation method of power grid investment based on historical investment effect			Calculation method of distribution network investment based on new power system		
		Investment scale (ten thousand dollars)	Deviation rate (%)	Average deviation rate (%)	Investment scale (ten thousand dollars)	Deviation rate (%)	Average deviation rate (%)
2018	17.68	17.08	3.44	7.46	18.17	2.79	2.33
2019	28.75	31.01	7.86		28.57	0.61	
2020	26.09	23.63	9.42		25.62	1.79	
2021	18.41	16.73	9.13		19.17	4.14	

and only the peak, flat, and valley electricity prices are considered, and the daily charge and discharge income is calculated as shown in Eqs. 31–33:

$$I_{tl} = P_f - P_c \quad (31)$$

$$P_c = S(p_m + p_l) \quad (32)$$

$$P_f = 2S\eta p_h \quad (33)$$

In the formula: I_{tl} is the peak-valley arbitrage income. P_f is the discharged income. P_c is the charging fee. S is the rated capacity of energy storage on the user side. p_h is the peak electricity price. p_m is the flat section electricity price. p_l is the low price of electricity. η is the charge-discharge efficiency.

6.3 Policy subsidy income

Policy subsidy income I_{bt} is calculated according to the regional energy storage subsidy scheme.

6.4 Case analysis

6.4.1 Grid investment scale in historical years

The distribution network investment calculation method based on historical investment results (Li et al., 2019) and based on the new power system are respectively used to calculate the investment scale of the county's power grid in the current year.

Based on the actual power grid investment scale from 2018 to 2021, the maximum deviation rate of the distribution network investment calculation method based on historical investment results is 9.42%, and the average deviation rate is 7.46%. But based on the new power system investment calculation, the maximum deviation rate is 4.14%, and the average deviation rate is 2.33%. The details are shown in Table 2.

The calculation results show that, compared with the distribution network investment calculation method based on historical investment results, the deviation rate of the distribution network investment calculation method based on the new power system is significantly smaller, and the investment scale is closer to the actual investment completion.

6.5 Grid investment scale in the coming years

Taking a county as a demonstration area, the investment scale of the county's distribution network based on the new power system is predicted in 2022.

6.5.1 Investment calculation on the power supply side

The county is a Class C power supply area. In 2022, the installed capacity of distributed power supply in the county will reach 30 MVA, the current line can accommodate an installed capacity of 11.7 MVA, and the remaining capacity needs to be absorbed by new lines and distribution transformers. The variable side distributed installed capacity is 11.9 MV A. In 2022, the county's power supply side investment is 3.6809 million dollars, and the details are shown in Table 3.

6.5.2 Grid side investment calculation

1) Calculation of power grid investment demand

In 2022, the county's power grid investment demand is 18.3998 million dollars, and the specific results are shown in Table 4.

Taking the highest electricity load of the whole society as an example, the sensitivity analysis of the index is carried out. In 2022, the highest electricity load in the whole society will increase by 8% compared with 2021. Assuming other conditions remain

TABLE 3 Calculation results of investment scale on the power supply side.

Category	Project name	Data	Data value	Investment (ten thousand dollars)	Total investment (ten thousand dollars)
Distributed power investment	New investment on the 10 kV line side	Length of overhead line (km)	10	62.76	189.85
		Cable line length (km)	5	70.61	
		Column switch (pcs)	12	11.30	
		Ring network room (box) (seat)	3	23.54	
		Cable branch box (seat)	3	4.71	
		Overhead branch line (km)	2.4	11.30	
		Cable branch line (km)	0.6	5.65	
		Overhead card neckline (km)	0.5	3.14	
		Overhead bare conductor line (km)	1.20	7.53	
	10 kV line side transformation investment	Overhead old line (km)	1.3	8.16	18.83
		Cable card neckline (km)	0	0.00	
		Old cable line (km)	0	0.00	
		Change on the column	12	18.83	
	New investment on the distribution transformer side	Overhead low voltage line (km)	9.6	15.06	107.63
		Power distribution room/block change (block)	5	23.54	
		Cable low-voltage line (km)	8	50.21	
	Distribution transformer side transformation investment	Old distribution transformer (Taiwan)	20	31.38	51.78
		Old low-voltage overhead line (km)	13	20.40	
		Old low-voltage cable line (km)	0	0	
Centralized power investment				0	0
Total					368.09

TABLE 4 Calculated results of power grid investment demand scale.

Key influencing factors	Measured value of decision coefficient	Grid investment in 2021 (ten thousand dollars)	Actual value in 2021	2020 actual value	Forecast for 2022	Forecast value of power grid investment in 2022 (ten thousand dollars)	Power grid investment in 2022 (ten thousand dollars)
GDP (ten thousand dollars)	0.2615	1,753.67	131.03	122.23	140.46	491.60	1,839.98
Number of power supply households (households)	0.0333		50.33	50.32	50.34	372.27	
Electricity sales (100 million kWh)	0.5128		29.78	29.05	30.53	5,875.43	
Total profit (ten thousand dollars)	0.0634		1.97	1.77	2.19	123.75	
The highest load in the whole society (ten thousand kilowatts)	0.129		823.1	762	889.10	1,557.44	

TABLE 5 Sensitivity analysis results of the highest electricity load in the whole society.

Index	Planning scheme (ten thousand dollars)	Change in the growth rate of the highest load in the whole society (%)					
		−20	−10	−5	5	10	20
Predicted value of grid investment in 2022 (ten thousand dollars)	1839.98	137.41	138.44	138.96	139.99	140.51	141.54
Compared with the standard value (ten thousand dollars)		−61.51	−31.04	29.91	60.39	90.87	121.34
Relative change rate (%)		−3.34	−1.69	1.63	3.28	4.94	6.59

TABLE 6 Calculation results of power grid investment capacity.

Data	Data value (ten thousand dollars)
Net profit	45.69
Turn in profits	37.50
Depreciation	1738.44
Financing amount	1,082.92
Investment capacity	2,829.55

unchanged, a sensitivity analysis is carried out on the different growth rates of the highest electricity load in the whole society. The calculation results of the scale of power grid investment demand show that when the growth rate of the highest electricity load in the whole society changes between −20% and 20%, the predicted value of investment demand changes between −3.34% and 6.59%.

The changes in the forecast value of investment demand are shown in Table 5.

After calculation, GDP, electricity sales, and the highest load of the whole society are the most sensitive factors.

2) Calculation of power grid investment capacity

Using the investment capacity prediction model, it is estimated that the county's power grid investment capacity in 2022 will be 28.2955 million dollars. The specific results are shown in Table 6.

3) Calculation results of grid side investment

Taking into account the investment demand and investment capacity of the power grid in the region, the weights of the investment proportion calculated by the AHP method are 0.4 and 0.6 respectively, and considering the grid side investment correction coefficient of 0.95, the final investment on the grid side of the county in 2022 is 23.1204 million dollars.

6.6 Load-side saving investment calculation

In 2022, the maximum demand-side response load in the county is 30MW, and the demand-side load response coefficient is 0.7. Due to the interruptible load response, 30 km of new 10 kV overhead lines, 36 switches on the column, 7.2 km of overhead branch lines, 32 transformers on the column, and 32 km of overhead low-voltage lines can be reduced, saving investment of 3.5648 million dollars as shown in Table 7.

The annual fixed unit price of the electricity subsidy is 62.79 cents/kWh, the single response time is 2 h, and the number of responses in the whole year is 10 times. The demand response load in the county is 65,577kW, and the demand response cost is about 0.8231 million dollars.

To sum up, the load-side saving investment in 2022 is 2.7416 million dollars.

6.6.1 Energy storage side investment calculation

1) Investment scale of energy storage side

In this paper, the unit energy storage power cost is 0.3923 million dollars/MW, the unit energy storage capacity cost is 0.3138 million dollars/MWh, and the unit energy storage power operation and maintenance cost and unit energy storage capacity operation and maintenance cost are 6.276 dollars/kW. In 2022, the county's energy storage side investment will be 4.6741 million dollars, the details are shown in Table 8.

2) Energy storage side investment income

6.7 Delay grid construction

In this paper, the unit power cost of the distribution network is 0.1569 million dollars/MW, the charging and discharging efficiency is 81%, the fixed asset depreciation rate of the distribution equipment is 30%, and the rated power of the energy storage is 5 MW. According to Eq. 30, it can be

TABLE 7 Save investment due to interruptible load response in 2022.

Investment voltage level	Data	Data value	Investment (ten thousand dollars)	Total investment (ten thousand dollars)
Investment in high voltage equipment	Required Transformer Capacity (MW)	0	0	0
	Number of substations (seats)	0		
MV equipment investment	Overhead line length (km)	30	188.28	256.0608
	On-column switch (pcs)	36	33.8904	
	Overhead branch line (km)	7.2	33.8904	
Low-voltage equipment investment	On-column variation (units)	32	50.208	100.416
	Overhead low-voltage lines (km)	32	50.208	
Total				356.4768

TABLE 8 Calculation results of investment scale on the energy storage side.

Energy storage configuration	Energy storage rated power (MW)	Rated capacity of energy storage (MWh)	Investment (ten thousand dollars)
Power side energy storage configuration	0	0	0
Grid-side energy storage configuration	2.5	5	259.6695
User side energy storage configuration	2	4	207.7356
Total			467.4051

obtained that the delay of power grid construction is 0.1906 million dollars.

6.8 Peak and valley arbitrage income

In this paper, the peak electricity price is 14.59 cents/kWh; the trough electricity price is 3.36 cents/kWh, and the flat segment electricity price is 8.34 dollars/kWh. The rated capacity of the user-side energy storage is 4 MWh, the charging and discharging efficiency is 81%, and the energy storage system works 330 days a year. Then the Eqs. 31–33 can be obtained, the peak-valley arbitrage income is 0.1575 million dollars.

6.9 Energy storage subsidy income

The energy storage compensation standard in this area is 31.38 dollars/kW per year. After calculation, the energy storage subsidy income in this area is 0.1412 million dollars.

To sum up, in 2022, the energy storage side income in the region will be about 0.5678 million dollars, and the energy storage side investment in the region 2022 will be 4.1847 million dollars.

6.9.1 Calculation results of new power system investment in the demonstration area

The estimated scale of investment on the power supply side is 3.68 million dollars, the estimated scale of investment on the grid side is 23.1204 million dollars, the scale of saving investment on the load side is 2.7416 million dollars, and the estimated scale of investment on the energy storage side is 4.1847 million dollars.

According to the research idea of the new power system investment method, which can be obtained from Eq. 1, the total investment in the county's new power system in 2022 is estimated to be 28.2443 million dollars.

7 Conclusion

Considering the investment and construction needs of new elements on the source, grid, load, and storage sides, this paper innovatively constructs an investment scale calculation model based on the new power system on the four sides of the source, grid, load, and storage. On the power supply side: Considering factors such as lines, distribution and transformation distributed power access standards, safe and reliable operation, and grid construction standards in different power supply areas, develop a new energy grid investment scale calculation model that takes into account safety and economy. On the grid side: overall

consideration of regional investment needs and investment capacity, and research on the investment scale calculation model based on the three major financial statements, economic development and power demand. On the load side: Considering the interruptible load's participation in peak shaving and the corresponding demand subsidy policy, a load-side saving investment scale calculation model that takes into account the benefits of the delay in the construction of the distribution network and the corresponding demand is developed. On the energy storage side: Considering the configuration of energy storage capacity and energy storage subsidy policy, develop an energy storage side investment calculation model that takes into account the costs and benefits of energy storage. The four-side investment calculation method based on the new power system, load and storage, plays an important role in meeting the precision requirements of distribution network investment projects under the new situation and improving the investment efficiency of the power grid.

The research results are applied to the calculation of the investment scale of a new power system in a county in the future, and can accurately predict the investment scale of the next year. From the perspective of historical years, compared with the traditional distribution network investment calculation method, the calculation results of the four-side investment scale calculation method of the source network, load and storage are more accurate and have certain forward-looking results. In the future, the input data optimization model can be revised based on accumulated experience, providing more flexible investment plans for long-term construction investment decisions, continuously improving the accuracy of model prediction, and better adapting to the new energy-based distribution network under the "carbon peaking and carbon neutrality" goals. New power system planning investment decisions.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

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Author contributions

ZF was responsible for the specific work of this article. ZF and XL guided the work of this article. CD and FJ did some calculations. FJ and WJ collected data and calculated and compared the plans.

Funding

The authors acknowledge the funding of the State Grid Corporation of China's Science and Technology Project (JSB17202000260).

Acknowledgments

The corresponding author thanks State Grid Jiaxing Electric Power Supply Company and State Grid Zhejiang Electric Power Co., Ltd. Pinghu Power Supply Company's selfless support.

Conflict of interest

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 24 June 2022

ACCEPTED 18 July 2022

PUBLISHED 05 January 2023

CITATION

Gong X, Xi L and Yuan B (2023), A new
search direction of IPM for horizontal
linear complementarity problems.
Front. Energy Res. 10:977448.
doi: 10.3389/fenrg.2022.977448

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A new search direction of IPM for horizontal linear complementarity problems

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This study presents a new search direction for the horizontal linear complementarity problem. A vector-valued function is applied to the system of $xy = \mu e$, which defines the central path. Usually, the way to get the equivalent form of the central path is using the square root function. However, in our study, we substitute a new search function formed by a different identity map, which obtains the equivalent shape of the central path using the square root function. We get the new search directions from Newton's Method. Given this framework, we prove polynomial complexity for the Newton directions. We show that the algorithm's complexity is $O(\sqrt{n} \log \frac{n}{\epsilon})$, which is the same as the best-given algorithms for the horizontal linear complementarity problem.

KEYWORDS

linear complementarity, interior-point method, full-Newton step, complexity, HLCP

Introduction

Karmarkar (1984) found the first method of the interior point algorithm, so linear programming appeared as a dynamic field of research. Soon after, the interior point algorithm was able to resolve linear programming problems and other optimal problems such as semi-definite programming problems, high-order conic programming problems, and linear and nonlinear complementarity problems.

Then, Nesterov and Nemirovskii (1994) imported a new concept of self-concordant barrier functions to define the interior point method for solving the convex programming problem. In addition, Vieira (2007) proposed a different interior point algorithm using the kernel function.

It showed that linear complementarity problems have more significant adhibition in the economic field; the most significant model is the equilibrium model of the Arrow-Debreu market. (Kojima et al. (1992) proved that linear complementarity problems are equal to some models of equilibrium market, but that is not necessarily sufficient. Hence, Illés et al. (2010) analyzed the general linear complementarity problems' solvability.

Some special search directions play an important role in analyzing interior point algorithms.

A basic idea of primal-dual interior-point algorithms is to go through the central path to get the optimal solution. Later, Peng et al. (2002a) verified that the essence of Karmarkar's algorithm was just a special classical barrier function, which is a polynomial time algorithm. Later, Peng et al. (2002b) proposed a self-regular function and got the best iteration bound for a large-update algorithm for linear programming problems.

Moreover, Peng et al. (2002b) presented a new method for getting search directions called full-Newton methods; the new algorithm transformed the center equation $xs = \mu e$ using a function ϕ and then got the new search direction from Newton's method.

Because linear complementarity problems are closely related to linear programming problems (Karimi and Tuncel, 2020; Yamashita et al., 2021; Yang, 2022; Zhang et al., 2022a; 2022b), many interior-point algorithms (Mansouri et al., 2015) are designed from linear programming to linear complementarity problems, and all got polynomial time numerical results.

Furthermore, Wang and Bai (2009) and Wang and Bai (2012) proposed the second-order cone programming using a new full Nesterov-Todd step of the primal-dual method. Scheunemann et al. (2021) presented a barrier term for the infeasible primal-dual interior algorithm of small strain single crystal plasticity. Lu et al. (2020) proposed a two-step method for horizontal linear complementarity problems, and Asadi et al. (2019) presented a large-step infeasible algorithm for horizontal, linear complementarity problems.

The above-mentioned studies almost used the square root function, which obtained a form of the central path. The basic idea of the new function is named the difference of identity. In this study, we use the new square root function to define the search direction to solve horizontal linear complementarity problems and give the complementarity problems and give the complexity of the algorithm.

The interior algorithm of HLCP

Two square matrices $M, N \in \mathbb{R}^{n \times n}$ are given, and $q \in \mathbb{R}^n$ is a vector. The horizontal linear complementarity problems finds a pair of $x, y \in \mathbb{R}^n$, such that

$$\begin{cases} Ny - Mx = q, \\ x^T y = 0, \\ x \geq 0, y \geq 0. \end{cases} \quad (1)$$

In this section, we study the horizontal linear complementarity problems (HLCP) based on the central path method to get the search directions.

We assume that (1) meets the need of the following two assumptions (Darvay, 2003).

Interior point condition

There are two vectors such that

$$Nx^0 - My^0 = q, \quad y^0 > 0, \quad x^0 > 0.$$

The monotonic property

There are two matrices (N, M) such that

$$Ny - Mx = 0 \rightarrow x^T y \geq 0 \quad (x, y \in \mathbb{R}^n).$$

From the above two assumptions, we can conclude that there is a solution for HLCP. We find an approximate solution by solving the following system:

$$\begin{cases} Ny - Mx = q, \\ xy = 0, \quad x \geq 0, y \geq 0. \end{cases} \quad (2)$$

Using the path-following interior algorithm replaces the second equation of Eq. 2 with the parameterized equation $xy = \mu e$ ($\mu > 0$); then, we get the following system:

$$\begin{cases} Ny - Mx = q, \\ xy = \mu e. \end{cases} \quad (3)$$

With $\mu > 0$, we can get the unique solution $(x(\mu), y(\mu))$ from system (3), and we call $(x(\mu), y(\mu))$ the μ -center of horizontal linear programming problem. With μ running through all positive numbers and when $\mu \rightarrow 0$, the central path exists and we get a solution for the horizontal linear programming problems (Kheirfam and Haghighi, 2019).

Search directions for HLCP

Considering the continuously differentiable $\phi: \mathbb{R}^+ \rightarrow \mathbb{R}^+$ and the inverse function ϕ^{-1} , then (2.3) can be transformed into the following form:

$$\begin{aligned} Ny - Mx &= q \\ \phi\left(\frac{xs}{\mu}\right) &= \phi e \end{aligned}$$

Applying Newton's method yields new search directions. Let

$$\begin{cases} N\Delta y - M\Delta x = 0 \\ \frac{y}{\mu}\phi'\left(\frac{xy}{\mu}\right)\Delta x + \frac{x}{\mu}\phi'\left(\frac{xy}{\mu}\right)\Delta y = \phi(e) - \phi\left(\frac{xy}{\mu}\right) \end{cases} \quad (4)$$

Let $dx = \frac{v\Delta x}{x}$, $dy = \frac{v\Delta y}{y}$; then,

$$\mu v(dx + dy) = y\Delta x + x\Delta y \quad (5)$$

$$dx dy = \frac{\Delta x \Delta y}{\mu} \quad (6)$$

From (5) and (6), (4) can be written in the form

$$\begin{cases} \bar{N}dy - \bar{M}dx = 0 \\ dx + dy = pv \end{cases} \quad (7)$$

At this time, $\bar{M} = MXV^{-1}$, $\bar{N} = MYV^{-1}$, $V = \text{diag}(v)$.

We get different values for the pv from the φ function and obtain the search directions.

Now, for $pv = \frac{\varphi(e) - \varphi(v^2)}{v\varphi'(v^2)}$, we choose $\varphi(t) = t - \sqrt{t}$; then, from the new function, we get a new direction, and

$$pv = \frac{2(v - v^2)}{2v - e} \quad v \in \left(\frac{1}{2}, +\infty\right) \quad (8)$$

We define $qv = dx - dy$ from

$$(XV^{-1}dy)^T(YV^{-1}dx) = dx^T dy$$

and monotonicity

Furthermore, let $dx = \frac{pv+qv}{2}$, $dy = \frac{pv-qv}{2}$; then,

$$dx dx = \frac{p_v^2 - q_v^2}{4} \quad (9)$$

Primal-dual interior-point algorithm for HLCP

- 1) Let $\epsilon > 0$ be the accuracy parameter, $0 < \theta < 1$ the update parameter, $\theta = \frac{1}{27\sqrt{n}}$. Assume a strictly feasible point (x^0, y^0) , s.t. $\delta(x^0, y^0, \mu^0) < \tau$.
- 2) If $\bar{x}y \leq \epsilon$, then stop; otherwise, go to the next step.
- 3) According to (4), find (4) and $(\Delta x, \Delta y)$. We get $x = x + \Delta x$, $y = y + \Delta y$. Then, turn to step 2.

Convergence analyses

Lemma 4.1. Let (dx, dy) be a solution of (7). Then, we have $0 \leq d_x^T d_y \leq 2\delta^2$.

Proof. Because the pair $[N, M]$ is in the monotone HLCP, we conclude that

$$\delta^2 = \|pv\|^2 = \|dx + dy\|^2 = \|dx\|^2 + \|dy\|^2 + 2dx^T dy \geq 2dx^T dy.$$

That is, $d_x^T d_y \leq 2\delta^2$.

Lemma 4.2. Let $\delta = (x, y, \mu) < 1$ and $e - 2v < 0$. Then, $(x_+, y_+) > 0$.

Proof. Let

$$\forall \alpha \in [0, 1], \quad x_+(\alpha) = x + \alpha\Delta x, \quad y_+(\alpha) = y + \alpha\Delta y.$$

Therefore,

$$x_+(\alpha)y_+(\alpha) = xy + \alpha(y\Delta x + x\Delta y) + \alpha^2\Delta x\Delta y \quad (10)$$

From (5) and (6),

$$\frac{1}{\mu}x_+y_+ = v^2 + \alpha v(dx + dy) + \alpha^2 dx dy \quad (11)$$

Due (7) to (9),

$$\frac{1}{\mu}x_+y_+ = (1 - \alpha)v^2 + \alpha(v^2 + vp_v) + \alpha^2\left(\frac{p_v^2}{4} - \frac{q_v^2}{4}\right).$$

Furthermore, from (8),

$$v^2 + vp_v = v^2 + \frac{2(v^2 - v^3)}{2v - e} = \frac{(2v^2)}{2v - e} \quad (12)$$

From (11), we get

$$\frac{1}{\mu}x_+(\alpha)y_+(\alpha) = (1 - \alpha)v^2 + \alpha\left(e + \frac{(v - e)^2}{2v - e} + \alpha\frac{p_v^2}{4} - \alpha\frac{q_v^2}{4}\right) \quad (13)$$

From $e - 2v < 0$, we get $\frac{(v - e)^2}{2v - e} \geq -\frac{p_v^2}{4}$.

From (13), we obtain

$$\frac{1}{\mu}x_+(\alpha)y_+(\alpha) \geq (1 - \alpha)v^2 + \alpha\left(e - (1 - \alpha)\frac{p_v^2}{4} - \alpha\frac{q_v^2}{4}\right),$$

$$x_+(\alpha)y_+(\alpha) > 0 \rightarrow \|(1 - \alpha)\frac{p_v^2}{4} + \alpha\frac{q_v^2}{4}\| \leq 1.$$

Using $\|p_v\| \geq \|q_v\|$, $\delta^2 = \frac{\|pv\|^2}{4}$.

Then,

$$\|(1 - \alpha)\frac{p_v^2}{4}\| + \|\alpha\frac{q_v^2}{4}\|_{\infty} \leq (1 - \alpha)\frac{\|p_v\|_{\infty}^2}{4} + \alpha\frac{\|q_v\|_{\infty}^2}{4}.$$

Therefore, we get a conclusion that, for any $\alpha \in [0, 1]$, the inequality $x_+(\alpha)y_+(\alpha) > 0$ holds, which signifies that the signs of $x_+(\alpha)$ and $y_+(\alpha)$ do not change on the interval $[0, 1]$. Hence, $x_+(0) > 0$, $y_+(0) > 0$ leads to $x_+(1) > 0$, $y_+(1) > 0$.

Lemma 4.3. Let $f: D \rightarrow (0, +\infty)$ be a decreasing function, where $D = [d, +\infty]$, $d > 0$.

Furthermore, let $v \in \mathbb{R}_+^N$ such that $\min(v) > d$. Then,

$$\|f(v) \cdot (v - e^2)\| \leq f(\min(v)) \cdot \|e - v^2\| \leq f(d) \|e - v^2\|.$$

Proof.

$$\begin{aligned} \|f(v) \cdot (e - v^2)\| &= \sqrt{\sum_{i=1}^n (f(v_i))^2 (1 - v_i^2)^2} \\ &\leq f(\min(v)) \cdot \sqrt{\sum_{i=1}^n (1 - v_i^2)^2} \\ &= f(\min(v)) \cdot \|e - v^2\| \\ &\leq f(d) \cdot \|e - v^2\|. \end{aligned}$$

Lemma 4.4. Let $\delta = \delta(x, y, \mu) < \frac{1}{2}$, $2v - e > 0$. Then,

$$v_+ > \frac{1}{2}e, \quad \delta = \delta(x_+, y_+, \mu) \leq \frac{3 - 3\delta^2 - 3\sqrt{1 - \delta^2}(1 - 2\delta^2)}{3 - 4\delta^2}.$$

Proof. From Lemma 4.2, we get

$$x_+ > 0, y_+ > 0, v_+ = \sqrt{\frac{x_+ y_+}{\mu}}.$$

Due to (4.4), as $\alpha = 1$, we get

$$v_+^2 = e - \frac{e - 2v - v^2}{2v^2} \cdot \frac{p_v^2}{4} - \frac{q_v^2}{4} \quad (14)$$

From $2v - e > 0$ and $v^2 + 2v - e > 0$, that is $v_+^2 \geq e - \frac{q_v^2}{4}$, then

$$\min(v_+) \geq \sqrt{1 - \frac{1}{4} \|q_v\|_{\infty}^2} \geq \sqrt{1 - \frac{\|q_v\|^2}{4}} = \sqrt{1 - \delta^2} \quad (15)$$

By using the function $f(t) = \frac{t}{(2t-1)(1+t)} > 0$ for any $t > 0.5$, $f'(t) < 0$, f is monotone decreasing.

From Lemma 4.3,

$$\delta(x_+, y_+, \mu) \leq \frac{\sqrt{1 - \delta^2}}{2(1 - \delta^2) + \sqrt{1 - \delta^2} - 1} \cdot \|e - v_+^2\| \quad (16)$$

Substituting $\sqrt{1 - \delta^2}$ and making reductions, we get

$$f(\sqrt{1 - \delta^2}) = \frac{1 - \delta^2 - \sqrt{1 - \delta^2}(1 - 2\delta^2)}{\delta^2(3 - 4\delta^2)} \quad (17)$$

We have $1 < \frac{t^2+2t-1}{t^2} < 2$ for all $t > \frac{1}{2}$.

Moreover, $e - v_+^2 = \frac{e-2v-v^2}{2v^2} \cdot \frac{p_v^2}{4} + \frac{q_v^2}{4}$.

Thus,

$$\|e - v_+^2\| \leq 2 \left\| -\frac{p_v^2}{4} \right\| + \left\| -\frac{q_v^2}{4} \right\| = 3\delta^2 \quad (18)$$

Using (16), (17), we obtain

$$\delta(x_+, y_+, \mu) \leq \frac{(3 - 3\delta^2 - 3\sqrt{1 - \delta^2})(1 - 2\delta^2)}{3 - 4\delta^2}.$$

Furthermore,

$$\delta(x_+, y_+, \mu) \leq \frac{3 - (1 - \sqrt{1 - \delta^2})}{3 - 4\delta^2} + \frac{3\delta^2(-1 + 2\sqrt{1 - \delta^2})}{3 - 4\delta^2}.$$

Let $\varphi_1(\delta) = \frac{3(1 - \sqrt{1 - \delta^2})}{3 - 4\delta^2}$, $\varphi_2(\delta) = \frac{3\delta^2(-1 + 2\sqrt{1 - \delta^2})}{3 - 4\delta^2}$.

For $\delta < \frac{1}{2}$ and then $4\delta^2 < 1$, $\frac{1}{3 - 4\delta^2} < \frac{1}{2}$, we obtain

$$\frac{1}{3} \varphi_2(\delta) < \frac{4 - 2\sqrt{3}}{2} \delta^2 \quad (19)$$

A simple calculus yields

$$\frac{1}{3} \varphi_2 < \frac{4 - 2\sqrt{3}}{2} \delta^2 \quad (20)$$

We have (19), (20).

We have $\frac{1}{3}(\varphi_1(\delta) + \varphi_2(\delta)) < \frac{4 - 2\sqrt{3} + \sqrt{3}}{2} \delta^2 = \frac{3 - \sqrt{3}}{2} \delta^2$.

Lemma 4.5. Let $\delta = \delta(x, y, \mu)$ and suppose that the vectors x_+ and y_+ are obtained using a full-Newton step. Thus, $x_+ = x + \Delta x$, $y_+ = y + \Delta y$. We get $(x_+)^T y_+ \leq \mu(n + 3\delta^2)$.

If $\delta < \frac{1}{2}$, then we obtain $(x_+)^T y_+ \leq \mu(n + \frac{3}{4})$.

Lemma 4.6. Let

$$\delta = \delta(x, y, \mu) < \frac{1}{2}, v > \frac{1}{2}, \mu_+ = (1 - \theta)\mu, v' = \sqrt{\frac{x_+ \theta_+}{\mu_+}}, \gamma = \sqrt{1 - \theta}, (0 < \theta < 1),$$

then $v' > \frac{1}{2}e$ and $\delta(x_+, y_+, \mu_+) < \frac{\sqrt{3}(\theta\sqrt{n} + 3\delta^2)}{-2\gamma^3 + \sqrt{3}\gamma^2 + 3\gamma}$.

If $\theta = \frac{1}{27\sqrt{n}}$, $n \geq 4$, we have $\delta(x_+, y_+, \mu_+) \leq \frac{1}{2}$.

Proof. $v' = \frac{1}{\gamma}\mu_+$ from Lemma 4.4 $\mu_+ > \frac{1}{2}e$, $\mu' > \frac{1}{2}e$.

Consider $h(t) = \frac{t}{(2t - \gamma)(\gamma + t)}$, ($t > \frac{\gamma}{2}$); we get

$$\frac{v' - v'^2}{2v' - e} = \frac{1}{\gamma} h(v_+)(\gamma^2 e - v_+^2).$$

For $h'(t) < 0$, for $h'(t) < 0$, we get that h is a decreasing function.

Using (4.9), we have

$$\begin{aligned} \|\gamma^2 e - v_+^2\| &= \|(1 - \theta)e - v_+^2\| \leq \| -\theta e \| + \|e - v_+^2\| < \theta\sqrt{n} + 3\delta^2 \\ \delta(x_+, y_+, \mu_+) &\leq \frac{\sqrt{3}(\theta\sqrt{n} + 3\delta^2)}{-2\gamma^3 + \sqrt{3}\gamma^2 + 3\gamma}. \end{aligned}$$

Using $g(\gamma) = \frac{1}{-2\gamma^3 + \sqrt{3}\gamma^2 + 3\gamma}$, $\gamma \in (0, 1)$, we have

$$g'(\gamma) = \frac{6\gamma^2 - 2\sqrt{3}\gamma - 3}{(-2\gamma^3 + \sqrt{3}\gamma^2 + 3\gamma)^2} < 0 \quad (0 < \gamma < 1).$$

This implies that g is decreasing.

We get $\delta(x_+, y_+, \mu_+) \leq \sqrt{3}(\frac{1}{27} + \frac{3}{4})\sqrt{\frac{53}{54}} < \frac{1}{2}$.

Lemma 4.7. We assume that the (x^0, y^0) is strictly feasible $\mu^0 = \frac{(x^0)^T y^0}{n}$ and $\delta(x^0, y^0, \mu) < \frac{1}{2}$, and assume that the two vectors x^k and y^k are obtained by the algorithm; then, after k iterations k and $(x^k)^T y^k \leq \epsilon$.

Proof. From lemma 4.5,

$$(x^k)^T y^k < \mu^k \left(n + \frac{3}{4}\right) = (1 - \theta)^k \mu^0 \left(n + \frac{3}{4}\right) \leq \epsilon.$$

Taking logarithms on two sides, then we get

$$k \log(1 - \theta) + \log\left(\mu^0 \left(n + \frac{3}{4}\right)\right) \leq \log \epsilon.$$

From $\theta \leq -\log(1 - \theta)$, we obtain

$$k\theta \geq \left(\mu^0 \left(n + \frac{3}{4}\right)\right) - \log \epsilon = \log \frac{\mu^0 \left(n + \frac{3}{4}\right)}{\epsilon}.$$

Because the self-dual embedding allows us to propose without any loss of generality that $x^0 = y^0 = e$, we have $\mu^0 = 1$.

Theorem 4.1. Suppose that $x_0 = y_0 = e$. If we consider the default values for θ and τ , we get that the algorithm just requires no more than $O(\sqrt{n} \log \frac{n}{\epsilon})$ interior-point iterations. The conclusion satisfies $x^T y \leq \epsilon$.

Conclusion and future works

This study proposed a primal-dual path-following algorithm for the horizontal linear complementarity problem based on a new search direction, which differs from those available. We

analyzed this algorithm and illustrated that the proposed algorithm has $O(\sqrt{n} \log \frac{n}{\epsilon})$ iteration complexity bound. Some interesting topics remain for future research. Firstly, we can extend the algorithm to linear complementarity problems over symmetric cones. Secondly, we can develop the infeasible interior point algorithm based on the method given in this study.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors without undue reservation.

Author contributions

XG: algorithm analysis; LX: astringency; BY: feasibility study.

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OPEN ACCESS

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 23 October 2022
ACCEPTED 29 November 2022
PUBLISHED 09 January 2023

CITATION
Gaojun M, Yanwen D, Pau G, Linlin Y and
Wenyi T (2023), Multi-objective capacity
optimization configuration of
independent wind-photovoltaic-
hydrogen-battery system based on
improved MOSSA algorithm.
Front. Energy Res. 10:1077462.
doi: 10.3389/fenrg.2022.1077462

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Multi-objective capacity optimization configuration of independent wind-photovoltaic-hydrogen-battery system based on improved MOSSA algorithm

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Under the background of large-scale and rapid development of renewable energy, in order to improve the economic benefit of the system and ensure the reliability of the system, this paper introduces hydrogen production and energy storage into the independent wind/photovoltaic/hydrogen/storage capacity optimization configuration method. In order to minimize the total planning cost and self-sufficiency rate of system power supply, a capacity optimization allocation model was established. On the basis of this model, the Multi-objective Salp Swarm Algorithm (MOSSA) was improved in Algorithm structure, Tent chaotic mapping was introduced to initialize the population, and the positions of leaders and followers were updated based on the adaptive spiral search strategy. The validity of the algorithm is verified by test function. Finally, the specific example is solved by MATLAB programming, and the improved multi-objective Salp Swarm Algorithm (IMOSSA) is used to obtain the capacity configuration scheme, which provides reference for the optimization design of independent photovoltaic hydrogen storage system.

KEYWORDS

renewable energy, hydrogen storage, capacity configuration, IMOSSA algorithm, multi-objective

1 Introduction

The goal of “striving to achieve carbon peak by 2030 and carbon neutralization by 2060” defines the direction of green and low-carbon development of power system under the goal of “double carbon” (Qiu et al., 2021; Wu et al., 2021). Wind energy and light energy are the representatives of renewable clean energy at present, which have the advantages of renewable, not limited by region, and are complementary in time and space (Chen and Sun, 2021; Dar et al., 2022). However, in practical applications, they are generally attached with energy storage devices to balance power fluctuations due to the randomness of meteorological conditions leading to the instability of the output power of

wind-solar complementary power generation (Zhao et al., 2021; Zhang et al., 2022). Therefore, it is an urgent challenge for the independent wind power storage system to reasonably configuration. The fan capacity, photovoltaic panel capacity and energy storage capacity so as to improve the economy and reliability of the system.

In the past few years, the topic of independent wind power storage system capacity optimization configuration has been widely discussed and a large number of research results have been obtained. In Reference (Yao et al., 2020), Monte Carlo simulation was used to deal with the uncertainty of wind, light and load, and the universal gravitation search algorithm is used for global optimization to get the optimal allocation scheme of wind, light and storage. In Reference (Liu et al., 2019), an optimal configuration model considering the whole life cycle cost of the system was proposed. The mixed decimal genetic algorithm with integer variables was adopted to solve the model, and the optimal capacity allocation of distributed power generation and energy storage devices is obtained. In Reference (Lin et al., 2021), the battery and supercapacitor are introduced into the wind-solar complementary power generation system as energy storage devices, and the configured energy storage capacity is obtained by using the improved quantum particle swarm optimization algorithm to minimize the monthly average life cycle cost. In Reference (Xu et al., 2006), taking the installation cost of the system as the target and the power supply reliability as the constraint, the constraint is dealt with by adaptive penalty function method through genetic algorithm optimization including elite strategy. At the same time, the type and capacity of wind turbine, the capacity and inclination angle of photovoltaic panel and the capacity of storage battery are optimized. Currently, the independent landscape storage system capacity optimization configuration mostly focuses on fans, photovoltaic panels and batteries, and few literatures apply hydrogen storage energy to the combined power supply system. Hydrogen energy has the advantages of green environmental protection, high power density and low maintenance cost. The combined energy storage form of battery and hydrogen energy storage can effectively make up for the shortcomings of the battery energy storage device, such as limited capacity, low power density and large maintenance, and greatly improve the performance of the energy storage device.

Therefore, the capacity optimization configuration of wind/photovoltaic/hydrogen/storage joint power supply system is studied, and a capacity optimization configuration method based on improved Salp sea sheath group algorithm is proposed. First of all, the hydrogen energy storage system is introduced into the independent wind and solar energy storage system, and the capacity optimization configuration model is constructed with the goal of minimizing the total annual planning cost and the self-supporting loss rate of the system power supply. Secondly, the structure of MOSSA algorithm is

improved, including the introduction of Tent chaotic map for population initialization, the use of adaptive spiral search strategy for group location update, and the use of test functions to verify the effectiveness of the algorithm. Finally, according to the annual measured landscape data and load data of a certain place, the model is solved by MATLAB software under the action of power generation control strategy, and the capacity allocation scheme of each unit of the system is obtained, which provides a reference for the optimal design of independent wind storage system.

2 New energy grid-connected model

Independent wind-photovoltaic-hydrogen-battery system consists of power generation unit, energy storage unit, electricity load and other necessary components of power system. The power generation unit includes a fan and a photovoltaic battery board, and the energy storage unit includes a storage battery and a hydrogen energy storage device. The hydrogen energy storage device is composed of a hydrogen storage tank, a fuel cell and an electrolytic cell, and its structure is shown in Figure 1.

2.1 Fan output model

The output power P_{wt} of wind turbine mainly depends on the variation of wind speed v , and its functional relationship can be approximately expressed by Eq. 1.

$$P_{WT}(t) = \begin{cases} 0 & v(t) < v_{in}, v(t) \geq v_{out} \\ P_{rated} \times \frac{v(t)^3 - v_{in}^3}{v_{rated}^3 - v_{in}^3} & v_{in} \leq v(t) \leq v_{rated} \\ P_{rated} & v(t) \leq v_{out} \end{cases} \quad (1)$$

Wherein, $P_{WT}(t)$ is the output power of the wind turbine at time t ; $v(t)$ represents the wind speed at the time t ; v_{in} , v_{rated} and v_{out} represent the cut-in wind speed, rated wind speed and cut-out wind speed of the wind turbine respectively; P_{rated} represents the rated power of the wind turbine.

2.2 Photovoltaic panel output model

The output power of photovoltaic array is mainly related to light intensity and temperature, and the expression of output power is as shown in Eq. 2:

$$P_{PV}(t) = P_{STC} \frac{G(t)}{G_{STC}} [1 + \varepsilon(T(t) - T_{STC})] \quad (2)$$

Wherein, P_{STC} , G_{STC} , and T_{STC} represent the maximum test power, light intensity and temperature under standard test

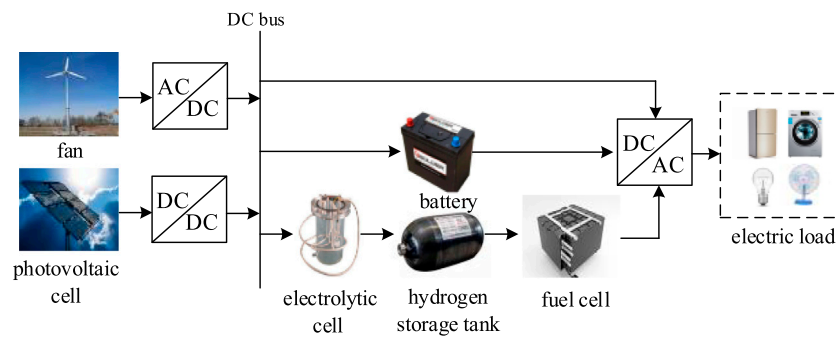


FIGURE 1
Independent wind-photovoltaic-hydrogen-battery system structure.

conditions (STC), $G(t)$, and $T(t)$ represent the actual solar light intensity and actual temperature at time t , respectively, and ε represents the power temperature coefficient.

2.3 Battery output model

During the charging and discharging process of the battery, the change of the charge state is as shown in Eq. 3:

$$\begin{cases} \text{SOC}_c(t) = (1 - \Delta) \cdot \text{SOC}(t-1) + \frac{P_c \cdot \eta_c}{E} \\ \text{SOC}_f(t) = (1 - \Delta) \cdot \text{SOC}(t-1) + \frac{P_f}{\eta_f \cdot E} \end{cases} \quad (3)$$

Wherein, $\text{SOC}_c(t)$ and $\text{SOC}_f(t)$ represent the SOC value of charging and discharging of the battery at time t respectively; Δ represents the self-discharge rate of the battery; $\text{SOC}(t-1)$ represents the charge state of the battery at the previous moment; P_c and P_f represent the charging and discharging power of the battery; η_c and η_f represent the charging and discharging efficiency of the battery, and 10% and 90%; E represents the rated capacity of the battery respectively. From the above formula, it can be deduced that the output model of the battery is:

$$\begin{cases} P_c(t) = \frac{[\text{SOC}_c(t) - (1 - \Delta) \cdot \text{SOC}(t-1)] \cdot E}{\eta_c} \\ P_f(t) = [(1 - \Delta) \cdot \text{SOC}(t-1) - \text{SOC}_f(t)] \cdot E \cdot \eta_f \end{cases} \quad (4)$$

2.4 Hydrogen energy storage device model

The models of electrolytic cell, hydrogen storage tank and hydrogen fuel cell can be expressed as follows:

$$P_{ele} = \frac{n_{H_2} \cdot H_{HHV}}{\eta_{ele}} \quad (5)$$

$$Q_{H_2} = n_{H_2} \cdot \eta_{tank} \quad (6)$$

$$P_{fc} = n_{H_2} \cdot H_{HHV} \cdot \eta_{fc} \quad (7)$$

Wherein, P_{ele} represents the input power of the electrolytic cell; n_{H_2} represents the hydrogen production capacity of the system; H_{HHV} represents the calorific value of hydrogen; η_{ele} represents the hydrogen production efficiency of the electrolytic cell, 70%; Q_{H_2} represents the hydrogen storage capacity of the hydrogen storage tank; η_{tank} represents the hydrogen storage efficiency of the hydrogen storage tank, 95%; P_{fc} represents the fuel cell output power; η_{fc} represents the conversion efficiency of the fuel cell, 65%.

3 Establishment of optimal configuration model

3.1 Objective functions

In this work, an optimization model is constructed with the goal of minimizing the annual total planning cost and the lowest self-supporting loss rate of the system power supply, to characterize the economy and reliability of the whole system, and to obtain the optimal capacity allocation scheme of fans, photovoltaic panels and energy storage devices, and thus, improving the economic benefits of the system and ensure the reliable operation of the system at the same time.

3.1.1 Total annual planning cost

The total annual planning cost f_1 of the system is mainly related to the equivalent annual fee of equipment installation ($C_{install}$), annual maintenance fee of equipment (C_{hold}), annual cost of equipment replacement ($C_{replace}$), loss cost of load and power shortage (C_{punish}), and penalty cost of abandoning wind and light (C_{loss}). The calculation formula is as follows:

$$f_1 = C_{install} + C_{hold} + C_{replace} + C_{punish} + C_{loss} \quad (8)$$

The annual cost of equipment installation, annual maintenance, replacement of equipment, loss of load and power, and penalty cost of abandoning wind and light can be expressed as:

$$\begin{cases} C_{install} = \sum_{i=1}^6 C_i \cdot N_i \cdot \frac{j(1+j)^{R_i}}{(1+j)^{R_i} - 1} \\ C_{hold} = \sum_{t=1}^{8760} \sum_{i=1}^6 k_i \cdot N_i \cdot P_i(t) \\ C_{replace} = \sum_{i=1}^6 C_i \cdot N_i \cdot \frac{j}{(1+j)^{R_i} - 1} \\ C_{punish} = k_p \cdot \sum_{t=1}^{8760} P_{drump}(t) \Delta t \\ C_{loss} = k_l \cdot \sum_{t=1}^{8760} P_{loss}(t) \Delta t \end{cases} \quad (9)$$

Wherein, C_i and N_i represent the number and unit price of each device, j represents the depreciation rate, R_i represents the service life of each device, k_i represents the maintenance cost coefficient of each device, $P_i(t)$ represents the power of each device at time t , k_p represents the unit loss cost of power outage, taking 0.3 yuan/kWh; k_p represents the unit abandonment wind and light penalty cost, taking 0.2 yuan/kWh; $P_{drump}(t)$ represents the system load power shortage power; and $P_{loss}(t)$ represents the power of abandoning wind and light in the system.

3.1.2 Self-sufficient loss rate of the power supply

The self-sufficient loss rate of the power supply represents the probability that the generating power of the system can not meet the local load demand in a certain period of time (Wu et al., 2014). In this work, the system power supply self-sufficiency loss rate is used as an index to characterize the system reliability. The smaller the system power supply self-sufficiency loss rate is, the higher the system reliability is. The expression is as shown in Eq. 10:

$$f_2 = \frac{\sum_{t=1}^{8760} [P_L(t) - (P_{WT}(t) + P_{PV}(t) + P_b(t) + P_{fc}(t))]}{\sum_{t=1}^{8760} P_L(t)} \quad (10)$$

Wherein, $P_L(t)$ represents the load power at time t ; $P_{WT}(t)$, $P_{PV}(t)$, $P_b(t)$ and $P_{fc}(t)$ represent the output power of fan, photovoltaic battery, battery and fuel cell at time t , respectively.

3.2 Constraint conditions

The constraint conditions of independent landscape storage combined power supply system are as follows:

$$\begin{cases} 0 < N_i \leq N_{imax} \\ Q_{H^2 \min} \leq Q_{H^2} \leq Q_{H^2 \max} \\ SOC_{\min} \leq SOC \leq SOC_{\max} \end{cases} \quad (11)$$

$$\begin{cases} 0 \leq P_c(t) \leq \left\{ P_{c \max}, \frac{E[SOC_{\max}(t) - (1 - \Delta) \cdot SOC(t - 1)]}{\eta_c} \right\} \\ 0 \leq P_f(t) \leq \left\{ P_{f \max}, [(1 - \Delta) \cdot SOC(t - 1) - SOC_f(t)] \cdot E \cdot \eta_f \right\} \end{cases} \quad (12)$$

Wherein, N_{imax} represents the maximum number of devices; $Q_{H^2 \min}$ and $Q_{H^2 \max}$ represent the lower limit and upper limit of hydrogen storage capacity of the hydrogen storage tank respectively; $SOC_{\min}$ and $SOC_{\max}$ represent the lower limit and upper limit of the battery charge state respectively; $P_{c \max}$ and $P_{f \max}$ represent the maximum charge and discharge power of the battery respectively.

4 System operation control strategy

The operation control strategy of pv/wind hydrogen storage system is shown in Figure 2. In this work, fans and photovoltaic panels are given priority to meet the load needs of users. According to the wind power generation and the user load, it can be divided into three situations: 1) if the wind power output can just meet the user load demand, there is no need for the energy storage system to intervene; 2) if the pv/wind output is greater than the user's load demand, priority will be given to charging the battery, and when the battery's charge state reaches the maximum value, the battery will stop charging, and if there is still any remaining power, the excess wind power will be obtained from the electrolytic cell and stored in the hydrogen storage tank until the capacity of the hydrogen storage tank reaches the upper limit; and 3) if the output of pv/wind is less than the load demand of the user, priority is given to replenishing the electricity through the output of the battery and the charge state of the battery is not lower than the minimum, if the output of the battery is not enough to meet the load demand, the hydrogen stored in the hydrogen storage tank is discharged through the fuel cell, and if the sum of the output power still can not meet the load demand, it will be removed according to the importance of the load.

5 Model solving methods

5.1 Salp swarm algorithms

Salp Swarm Algorithms (SSA) is a new heuristic optimization algorithm proposed by Professor Mirjalili et al. by simulating the individual and group behavior of ascidian in the ocean (Seyedali et al., 2017). In the deep sea, Salp sea squirts usually form a group called Salp sea sheath chain in order to quickly coordinate change and foraging. The Salp sea sheath chain can be divided into two groups:

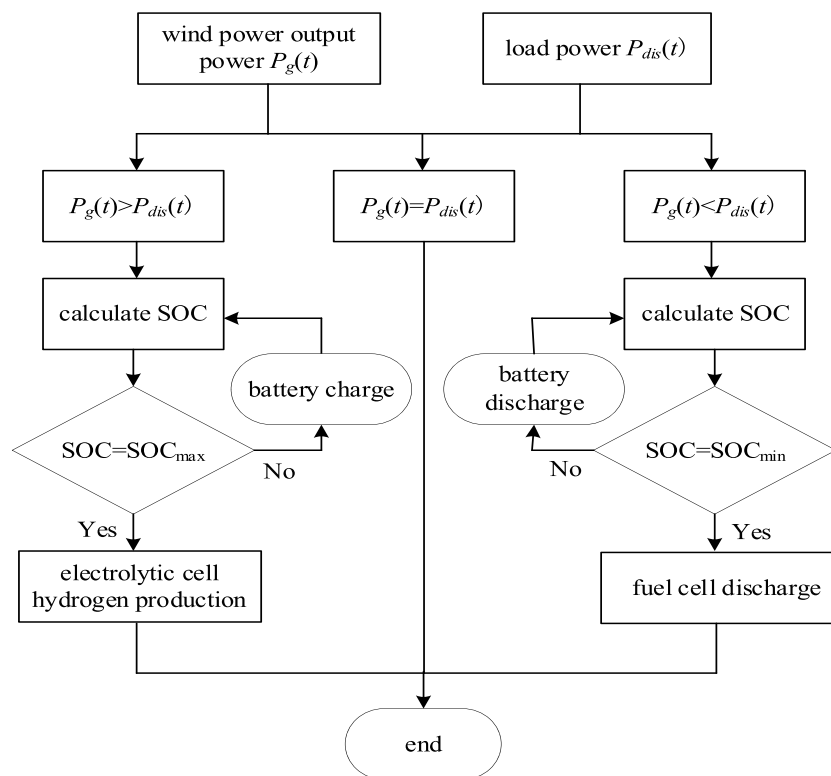


FIGURE 2
Flow chart of system running policies.

the leader at the front of the Salp sea sheath chain is responsible for finding the location of food; the rest of the Salp sea squirts are followers, connected from head to tail, following the leader, as shown in Figure 3. As the leader leads his followers closer to the food source, the algorithm gradually tends to the optimal solution.

The location update formula for leaders is as follows:

$$X_j^1 = \begin{cases} F_j + c_1 \left[(u_j - l_j) c_2 + l_j \right] & c_3 \geq 0.5 \\ F_j - c_1 \left[(u_j - l_j) c_2 + l_j \right] & c_3 < 0.5 \end{cases} \quad (13)$$

Wherein, X_j^1 represents the position of the first ascidian (leader) in dimension j , F_j represents the position of food source in dimension j , u_j , l_j represents the upper and lower bounds of dimension j , c_2 and c_3 represent random numbers in the range of $[0,1]$, and c_1 represents convergence factor, whose values are shown as follows:

$$c_1 = 2e^{-\left(\frac{l}{L}\right)^2} \quad (14)$$

Wherein, l represents the current number of iterations and L represents the maximum number of iterations.

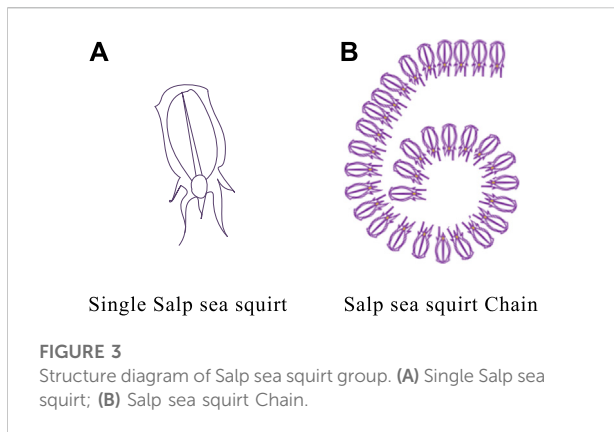
The location update formula for followers is:

$$X_j^i = \frac{1}{2} (X_j^i + X_j^{i-1}) \quad (15)$$

Wherein, X_j^i represents the position of the i th follower in the j th dimension of the space, and X_j^{i-1} represents the position of the $i-1$ -th follower in the j th dimension of the space, where $i \geq 2$.

5.2 Improved multi-objective salp sheath group algorithm

SSA algorithm can only be used to solve optimization problems with a single objective, while multi-objective optimization problems usually require a set of optimal solutions (non-dominant solution sets), whose objective vector set is the Pareto Frontier. Therefore, it is necessary to adjust the traditional SSA algorithm to solve the multi-objective problem. The MOSSA algorithm introduces the external file Archive to store the non-dominant solution of the current population. After each iteration, the algorithm will generate new individuals. Compare these individuals with the individuals in Archive one by one and update the individuals in Archive. The updating method is as follows: if the new individual dominates one or more individuals in the external file, the new individual will be added to the external file and the old individual dominated by it will be deleted. If the new individual is dominated by at least one



individual in the external file, the new individual does not join the external file; if the new individual and any individual in the external file do not dominate each other, the new individual joins the external file. According to the density of other solutions in the neighborhood of the non-dominant solution, the grade is determined. The more other solutions in the neighborhood, the higher the level of the non-dominant solution. Due to the limited capacity of the external file, the densest solution, that is, the solution with the highest level, is deleted when the external file is full. Roulette is used to determine the food source individuals that the next-generation of leaders will pursue. (Fan et al., 2020). Among them, if the two non-dominant solutions x_i and x_j in the external file are adjacent to each other, the following conditions must be met:

$$\begin{cases} |f_a(x_i) - f_a(x_j)| < H_a, \forall a \in A \\ H_a = \frac{f_a^{\max} - f_a^{\min}}{n_{\max}} \end{cases} \quad (16)$$

Wherein, f_a represents the value of the a th objective function, A represents the set of objective functions, H_a represents the neighborhood distance threshold of the a th objective function, $f_a^{\max}$ and $f_a^{\min}$ represent the maximum and minimum values of the a th objective function in the current external file, and $n_{\max}$ represents the limit value of the number of non-dominant solutions stored in the external file.

5.2.1 Tent chaotic map

In the process of initializing the population, the MOSSA algorithm usually uses the randomly generated data as the initial information of the population, which increases the premature risk of the algorithm and affects the optimization results of the algorithm. The initial value of the population with more uniform distribution can be obtained by using the ergodicity and randomness of chaotic motion, which is helpful for the algorithm to break away from the local optimal solution.

In this paper, Tent map, which has better chaotic characteristics than Logistic map, is introduced for population

initialization. (Zeng et al., 2017; Teng et al., 2018). Figure 4 shows the bifurcation diagram of the basic Tent mapping, but the Tent mapping is easy to fall into fixed points and small periodic cycles, so an improved Tent mapping formula is introduced as shown in Eq. 17.

$$x_{k+1} = \begin{cases} 2x_k & 0 \leq x_k \leq 0.5 \\ 2(1 - x_k) & 0.5 \leq x_k \leq 1 \end{cases} \quad (17)$$

The steps to initialize the Tent mapping are as follows:

- 1) Select the initial value x_0 randomly and prevent it from falling into the small periodic point {0.2, 0.4, 0.6, and 0.8}.
- 2) The reference Eq. 16, generates a set of x sequences, and $i = i + 1$ after the iteration is completed. If the maximum number of iterations is reached, jump directly to the last step.
- 3) If $x_i = \{0, 0.25, 0.50, 0.75\}$ or $x_i = x_{i-m}$, and where $m = \{0, 1, 2, 3, 4\}$, then make $x_i = x_i + 0.1 \cdot \text{rand}(0, 1)$ replace the original value and move on to the second step.
- 4) Stop running and keep the x sequence.

5.2.2 Spiral position update strategy

In the late iteration of the basic MOSSA algorithm, it is easy to have a slow local optimal convergence rate. In order to improve the local search ability of the algorithm, inspired by the tuna foraging algorithm in reference, (Lei et al., 2021), a spiral position update strategy is used to improve the location update of leaders and followers in the salp sea squirt group, and expand the search scope. This makes it easy to find more potential better solutions. (Zhao et al., 2020; Li and Wang, 2021).

5.2.2.1 Leader location update

The location update strategy takes 0.5 as the demarcation point, and the location update mode of the leader at the front end of the salp sea sheath chain is determined by a random probability rand in the random range of 0–1. When $\text{rand} < 0.5$, the original algorithm position update mode is selected, and when $\text{rand} \geq 0.5$, the spiral position update mode is selected.

The helix position is updated by:

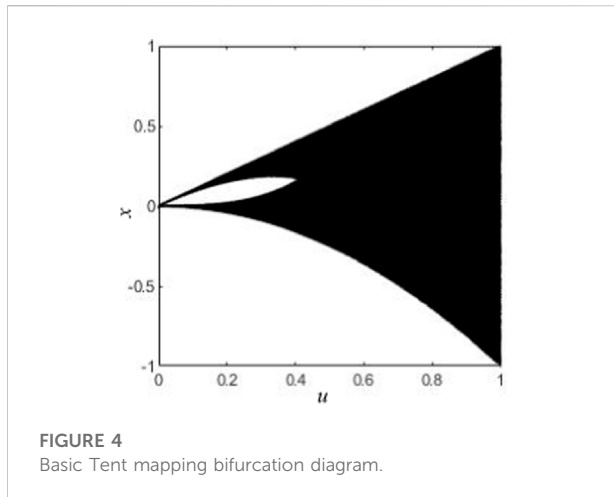
$$\begin{cases} X_j^1 = F_j + c_1 [(u_j - l_j)\beta + l_j] \\ \beta = e^{bl} \cos(2\pi b) \\ l = e^{3 \cos((t_{\max} + 1/t) - 1)\pi} \end{cases} \quad (18)$$

Wherein, b represents a random number, which is evenly distributed between 0 and 1; t represents the current number of iterations of the algorithm; $t_{\max}$ represents the maximum number of iterations of the algorithm.

5.2.2.2 Follower location update

The follower location is updated by:

$$X_j^i = F_j + \text{rand}(X_j^i - X_j^{i-1}) + \beta \cdot (F_j - X_j^{i-1}) \quad (19)$$



Where, rand represents the random number between [0,1].

5.3 Solving steps of improved algorithm

Using the IMOSSA algorithm to find the Pareto front, the specific steps to obtain the capacity optimization configuration results of the independent wind/light/hydrogen/storage system are as follows:

- (1) initialize the population. Firstly, the annual wind speed, solar light intensity, temperature, load time series data and the purchase unit price, unit installed capacity and maintenance cost coefficient of each device are introduced, and the algorithm parameters such as problem dimension dim , population size N , external archive scale $ArchiveMaxSize$, maximum number of iterations t_{max} , upper and lower limit u_j and l_j are set. Secondly, taking the number of each device as the decision variable, the chaotic sequence is generated by introducing Tent map within the constraint range, and the population is initialized according to the upper and lower limits of the search space.
- (2) According to the Eqs 8–12, the fitness values f_1 and f_2 of each individual are calculated according to the operation control strategy, and the external file Archive is updated according to the relationship between the new solution and the original non-dominant solution.
- (3) Judge whether the number of non-dominant solutions in the external file Archive exceeds the limit, if so, the density of other solutions in the neighborhood of each non-dominant solution is judged according to Eq. 16, and the solution with the highest density is deleted first. Otherwise, roulette is directly used to select a non-dominant solution from the external file as the food source individual to be pursued by the next-generation of leaders.
- (4) Update the position of the leader according to the Eqs 13, 18.

- (5) Update the position of the followers according to the Eq. 19.
- (6) Determine whether the algorithm reaches the maximum number of iterations, if so, output the pareto solution set, that is, the capacity optimization configuration scheme of the independent wind/light/hydrogen/storage system, otherwise turn to Step (2).

5.4 Algorithm performance test

In order to verify the performance of the improved algorithm IMOSSA, the standard test function ZDT1-ZDT4 (Li et al., 2021) is selected to analyze the algorithm qualitatively. Set the population size 100, the external archive capacity 200, and the maximum number of iterations 100. Figure 5 shows the comparison between the Pareto front and the real Pareto front of the IMOSSA algorithm on four test functions.

According to Figure 5, the pareto front obtained by the improved algorithm can be distributed around the real pareto front of the test function, and has good convergence and distribution. However, the superiority of the algorithm can not be shown directly by qualitative analysis, so the cec2009 series test function in reference (Fan et al., 2020) is selected to test, and the inverse generation distance (IGD) (Geng et al., 2019) is introduced to comprehensively evaluate the convergence and diversity of the algorithm. The smaller the IGD is, the better the result is. The test results are compared with those of MOSSA algorithm, NSGAI algorithm and MOPSO algorithm. The calculation formula of IGD is as follows:

$$IGD = \frac{\sum_{p \in P^*} d(p, P)}{|P^*|} \quad (20)$$

Wherein, P and P^* represent the Pareto Frontier solution set and the real Pareto optimal Frontier obtained by the algorithm, respectively; $|P^*|$ represents the number of individuals in P^* ; d represents the minimum Euclidean distance between individual p and P^* in P , respectively.

IMOSSA, MOSSA, NSGAI, and MOPSO are run 30 times on the UF1-UF7 test function respectively. The IGD of the solution set obtained by the four algorithms in each operation is recorded and the average value and standard deviation are calculated. The results are shown in Table 1. According to Table 1, compared with MOSSA, NSGAI and MOPSO, the mean and standard deviation of IGD in most of the test functions of IMOSSA algorithm are lower than those of the other three algorithms, that is, the convergence and diversity of IMOSSA algorithm are better than those of the other three algorithms, indicating that IMOSSA algorithm effectively improves the original algorithm and has more advantages in dealing with multi-objective problems.

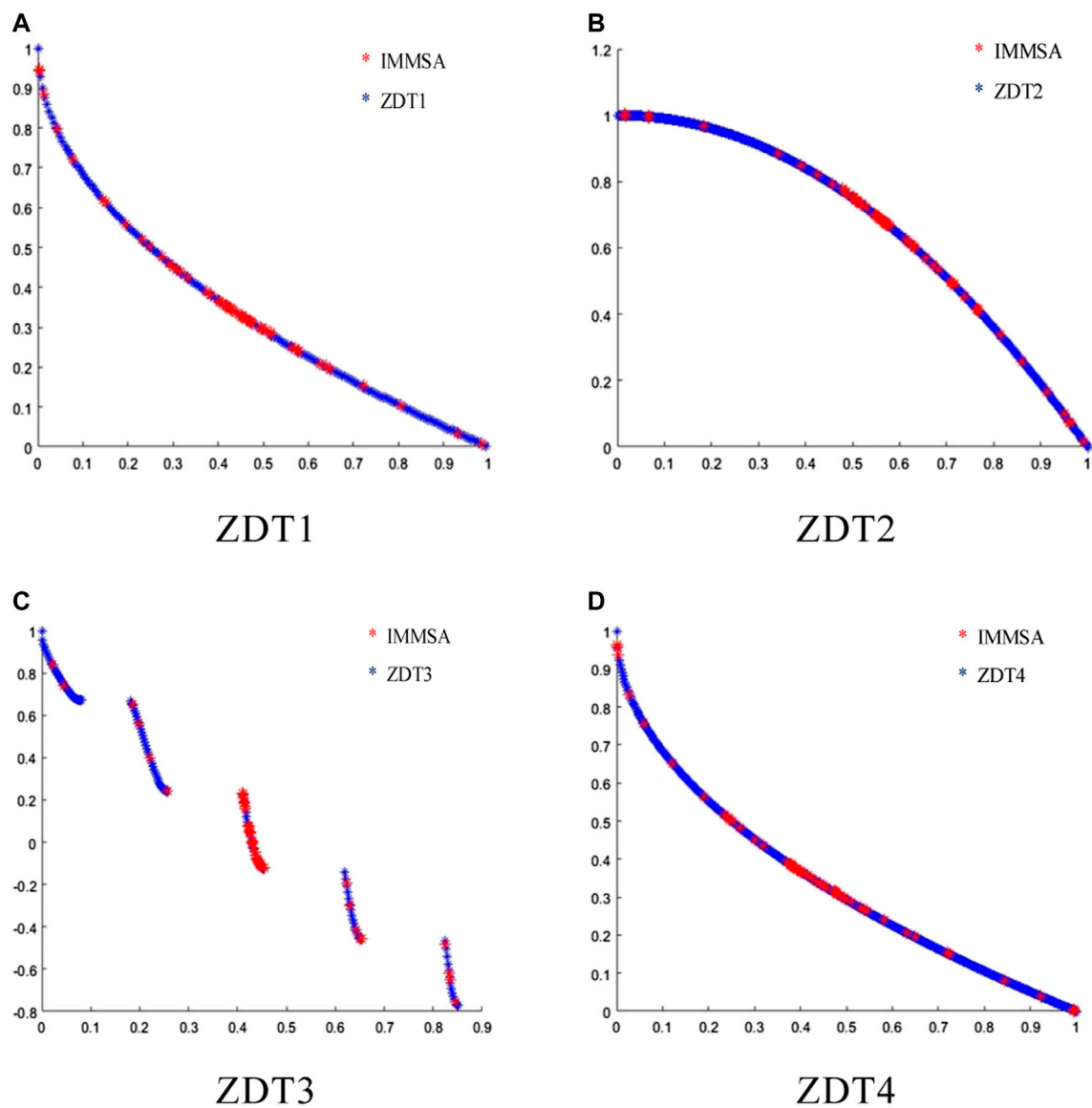


FIGURE 5
Basic Tent mapping bifurcation diagram. (A) ZDT1; (B) ZDT2; (C) ZDT3; (D) ZDT4.

6 Example analysis

6.1 Basic parameters

Based on the capacity optimization configuration model established above, the time series data of wind speed, solar light intensity, ambient temperature and load measured in a place in the whole year are introduced (as shown in Figure 6).

Based on the system operation control strategy, the IMOSSA algorithm is used to solve the optimization problem. Table 2 shows the relevant technical parameters of fan, photovoltaic

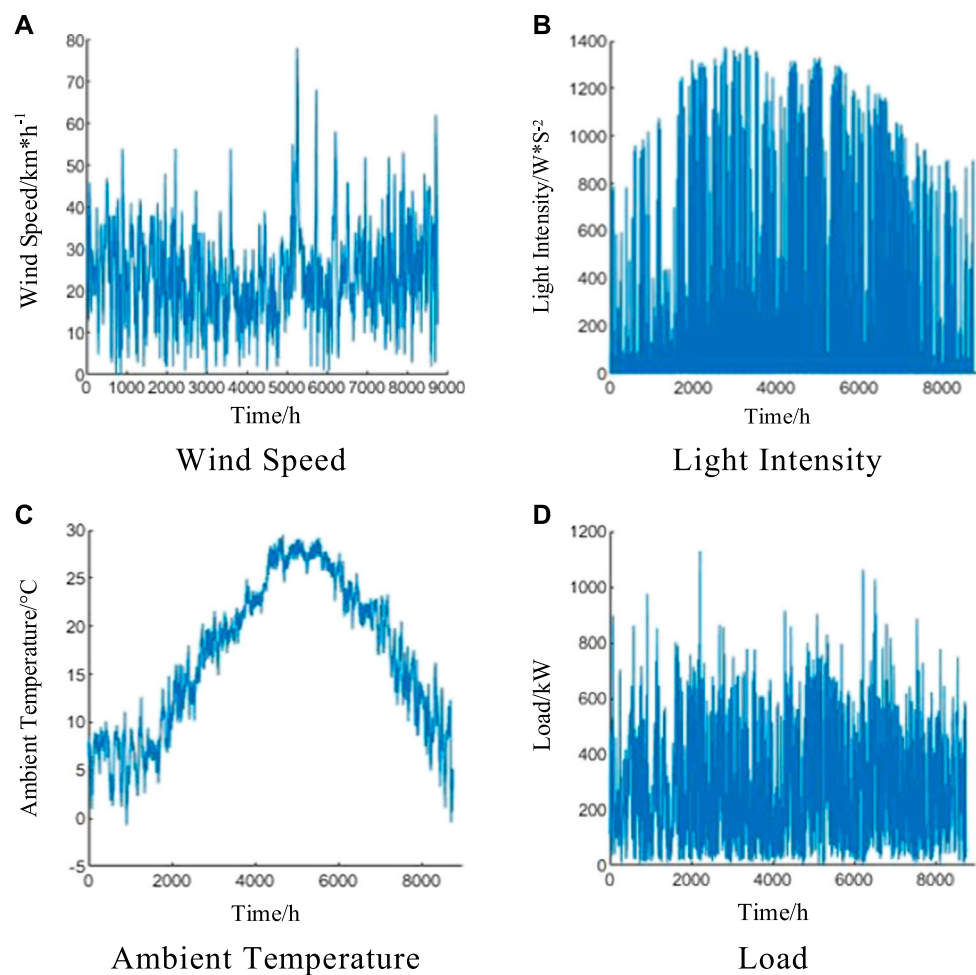
panel, storage battery, electrolytic cell, hydrogen storage tank and fuel cell.

6.2 Analysis of capacity optimization results

The initial parameters of IMOSSA algorithm are set as follows: the population size is 30, the number of iterations is 200, and the external file size is 50. Figure 7 shows the pareto optimal solution set obtained by MATLAB software

TABLE 1 Test results of four algorithms on test function.

Algorithms		UF1	UF2	UF3	UF4	UF5	UF6
IMO	Mean	0.0089	0.0069	0.1211	0.0082	0.0204	0.0965
SSA	SD	0.0018	0.0045	0.0803	0.0018	0.0135	0.0202
MO	Mean	0.0260	0.0268	0.1671	0.0241	0.0417	0.1175
SSA	SD	0.0125	0.0157	0.0926	0.0125	0.0223	0.0256
NSG	Mean	0.1118	0.0448	0.1638	0.0267	0.0378	0.1327
AII	SD	0.0240	0.0168	0.0769	0.0136	0.0224	0.0354
MO	Mean	0.1150	0.0504	0.2119	0.1240	0.0479	0.1475
PSO	SD	0.0275	0.0172	0.0846	0.0053	0.0264	0.0261

**FIGURE 6**

Weather and load data of a locality for 1 year. (A) Wind Speed; (B) Light Intensity; (C) Ambient Temperature; (D) Load.

TABLE 2 Related technical parameters of each device in the system.

Device	Single machine capacity	Purchase cost/yuan	Operation and maintenance cost factor/(yuan/kW h)	Replacement cost/yuan	Useful life/year
Air blower	3 kW	9,000	0.0187	7,000	20
PV battery board	0.2 kW	2,500	0.0079	2000	20
Accumulator battery	4 kW h	1,000	0.008	880	10
Electrolytic cell	5 kW	5,000	0.03	4,000	20
Hydrogen storage tank	1 kg	10,000	0	9,000	20
Fuel cell	1 kW	6,000	0.5	5,000	10

using IMOSSA, MOSSA, and NSGAI algorithms, respectively.

According to Figure 7, when the initial parameter values are the same, the Pareto Frontier obtained by IMOSSA algorithm is better than that of the other two algorithms, and the distribution of Pareto optimal solution is more dispersed and uniform, which verifies the effectiveness and necessity of algorithm improvement. Based on the topsis decision method, the system optimization Pareto solution set is decided, and the final result is the optimal solution. The capacity allocation scheme and the objective function values obtained by the three algorithms are shown in Tables 3, 4.

Generally, the annual total planning cost of the two sub-objective functions and the system power supply self-sufficiency loss rate contradict each other. When the system power supply self-sufficiency loss rate tends to zero, the required annual total planning cost reaches the peak. This is because the higher the planning cost of the system means that it can be equipped with more distributed power and energy storage devices, provide more spare capacity to meet the power supply needs of the load side, and effectively avoid the abandonment of wind and light or insufficient power of the system. As can be seen from the data in Table 4, the MOSSA algorithm configuration scheme is more economical than the NSGAI algorithm configuration scheme, and the total annual planning cost is reduced by 5.46%, but it is not dominant in terms of reliability, and the self-sufficient loss rate of the system power supply is reduced by 6.62%. Compared with the first two configuration schemes, the configuration scheme of IMOSSA algorithm is both economical and reliable, the total annual planning cost is reduced by 5.28% compared with MOSSA algorithm, and the self-sufficient loss rate of system power supply is reduced by 54.39% compared with NSGAI algorithm.

Figure 8 shows the comparison of wind turbine, photovoltaic panel power generation and load-side power demand. Obviously, the power supply of wind turbine and photovoltaic panels will be surplus after meeting the power

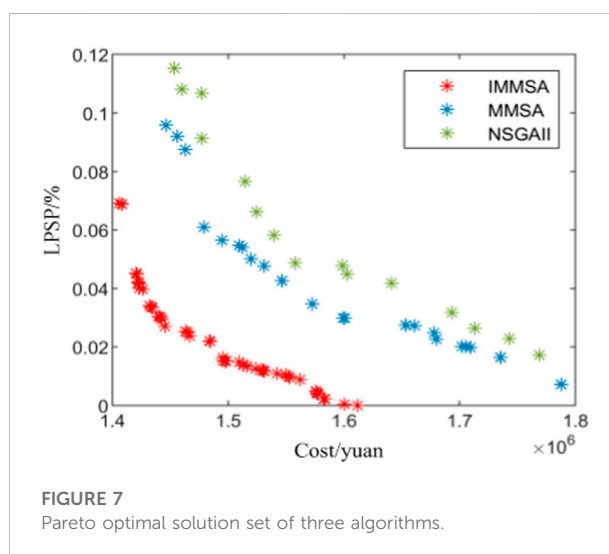


FIGURE 7
Pareto optimal solution set of three algorithms.

demand of the load end in most cases, but sometimes the wind power generation can not meet the demand of the load end, and the battery and hydrogen storage can store electric energy when the wind power resources are surplus, and supplement the power when the wind power generation is insufficient. Figure 9 shows the state diagram of the charge constant of a single energy storage battery for 1 year. It is obvious that the charge constant of the battery is more than 0.5 in spring and autumn, but lower in summer and winter, especially in summer. This is also in line with the reality, the summer electricity consumption is too much, the situation of power shortage is more obvious.

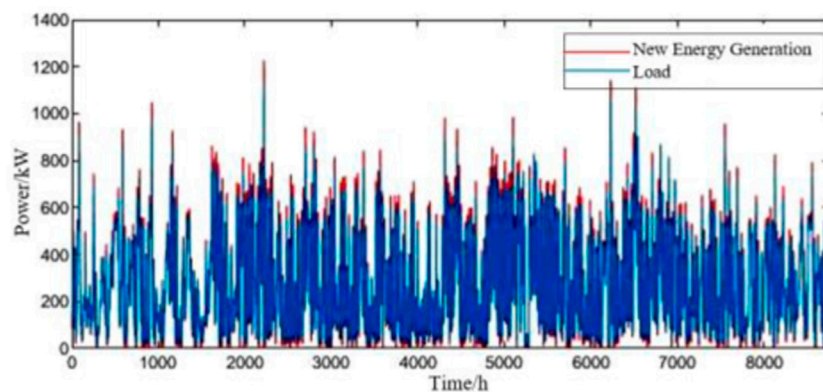
The change of the capacity ratio of the hydrogen storage tank is shown in Figure 10, which indicates the proportion of the existing hydrogen in the total hydrogen storage tank, which shows that the hydrogen content in the hydrogen storage tank is constantly changing, which further proves the effect of the hydrogen energy storage device on the power balance of the system. The power of electrolytic cell

TABLE 3 Capacity configuration schemes of three algorithms.

Algorithms	Fan/unit	Photovoltaic panel/block	Battery/set	Electrolytic cell/unit	Hydrogen storage tank/unit	Fuel cell/group
NSGAI	178	2,474	199	42	199	48
MOSSA	178	2,471	163	48	180	40
IMOSSA	178	2,466	157	51	175	39

TABLE 4 Objective function values of the three algorithms.

Algorithms	Total annual planning cost/yuan	Self-sufficient loss rate of system power supply/%
NSGAI	1,693,372	0.0317
MOSSA	1,600,948	0.0296
IMOSSA	1,516,471	0.0135

**FIGURE 8**
Comparison of wind power generation and load demand.

and fuel cell is shown in Figure 11, it can be seen that from October to November, the wind speed is larger, photovoltaic panels and batteries have been supplemented to basically meet the power demand of the load end, and most of the hydrogen storage tanks are in the full stage. From June to August, although the light intensity and ambient temperature are basically at the highest value of the year, the power demand of the load side also increases synchronously. When the wind output is less than the user load demand, the battery gives priority to the output. When the minimum SOC is reached, the hydrogen storage tank releases hydrogen to power through the fuel cell to reduce the load shortage. From January to March, the wind speed, light intensity and ambient temperature are low, the demand for electricity at the load end is high, and the battery can not meet the load demand, so it also needs the power supply of hydrogen storage device.

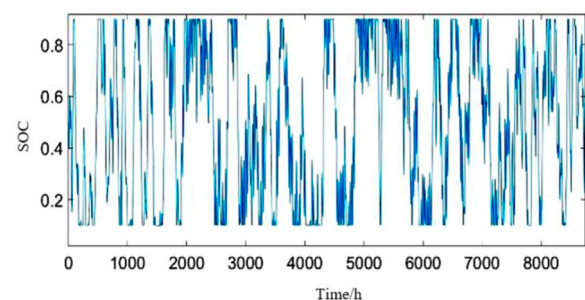
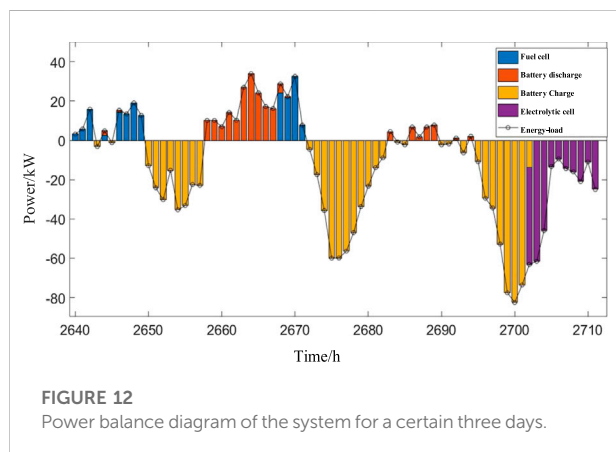
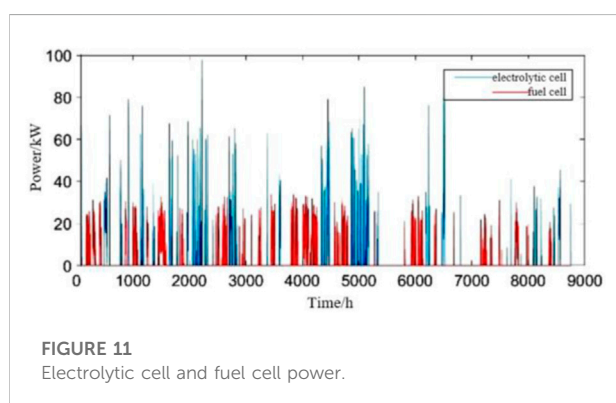
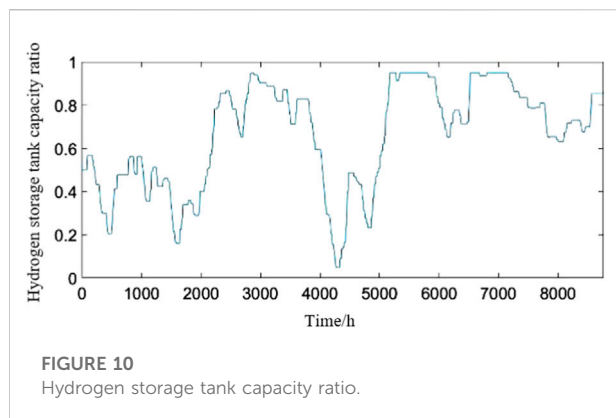
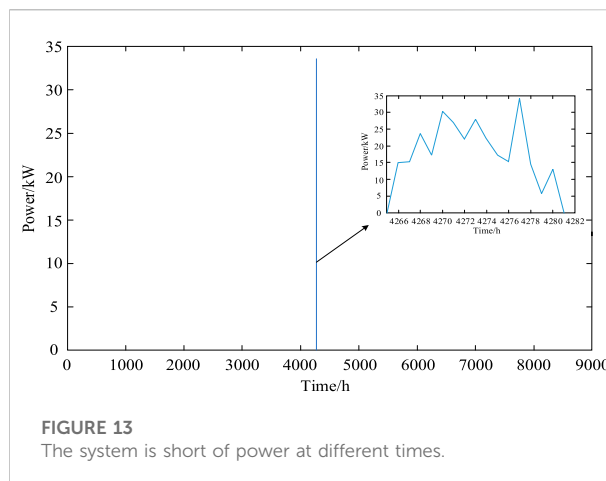
**FIGURE 9**
Charge state diagram of energy storage battery.

Figure 12 shows the power balance chart of the system for one 3 days. As can be seen from the chart, wind power generation is first used to meet the power load demand, and the rest depends



on battery and fuel cell supply. When the supply of wind power exceeds demand, the battery and electrolytic cell work to reduce the abandonment of wind and light. According to the power shortage power of the load at different times of the system (Figure 13), it can be seen that the proportion of the power shortage penalty cost of the system to the total cost is less than 1%, and the number of times that the system cannot meet the demand of the load side in the whole year is very few, and the



system can supply power to the load. Furthermore, it shows that the capacity configuration of the system is reasonable.

7 Conclusion

For independent wind-photovoltaic-hydrogen-battery system, the capacity optimization configuration model is constructed after considering the total annual planning cost of the system and the self-supporting loss rate of system power supply, and the improved multi-objective SSA is used to solve the model. Through the performance test of the algorithm and the simulation analysis of an example, the results show that:

- (1) The IMOSSA algorithm introduces Tent mapping and adaptive spiral search strategy, which makes the algorithm easy to break away from the local optimal solution and improves the convergence speed of the algorithm. In the algorithm performance test, it is better than MOSSA algorithm, NSGAI algorithm and MOPSO algorithm, and can better solve the multi-objective optimization problem.
- (2) The multi-objective optimal configuration of each device of wind/photovoltaic hydrogen storage system is carried out based on the scenery and load data of the selected area. In the case of low self-sufficient loss rate of power supply of the system, the annual planning cost of the system is reduced, the economy of the system is balanced with the reliability of power supply, and a reference is provided for the early design and planning of the independent wind hydrogen storage system.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, MG and YL; methodology, MG; software, YL; validation, DY, GP, and TW; formal analysis, GP; investigation, MG; resources, DY; data curation, TW; writing—original draft preparation, YL; writing—review and editing, MG; visualization, DY. All authors have read and agreed to the published version of the manuscript.

Funding

Project supported by the National Natural Science Foundation of China (51877101); Key research and development program of Jiangsu Province (BE2021094).

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 18 September 2022
ACCEPTED 24 October 2022
PUBLISHED 09 January 2023

CITATION
Zhao W, Cui A, Fang M, Yang L, Chen K
and Gong X (2023), State assessment of
110–220 kV intelligent substation based
on multisensor fusion algorithm control
and image vision.
Front. Energy Res. 10:1047359.
doi: 10.3389/fenrg.2022.1047359

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State assessment of 110–220 kV intelligent substation based on multisensor fusion algorithm control and image vision

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With the development of modern information technology, intelligent substation technology has been widely used, which greatly promotes the development of power grid. The information integration platform of intelligent substations realizes panoramic data collection and data sharing of substations. With the continuous development of the economy and society, it is crucial to improve the power regulation ability of intelligent substations, make scientific use of intelligent technology, and optimize the patrol level of intelligent substation patrol robots to better meet the operation needs of substations. In the actual substation construction, the flexibility of equipment utilization in intelligent substations should be fully considered. In addition, the number of substations should be controlled to improve the utilization efficiency of patrol robots. This paper mainly summarizes the monitoring technology of intelligent substations, the positioning technology of inspection robots, and the multi-sensor control technology to lay a foundation for the follow-up inspection work of intelligent substations.

KEYWORDS

state assessment, intelligent substation, multisensor fusion, algorithm control, image vision

Introduction

In recent years, with the development of power transmission and transformation technology around the world, the scale of the power grid has been continuously expanded, and the voltage level of power transmission and transformation has been continuously improved, which inevitably increases the number and complexity of power equipment, and the maintenance cost of equipment accounts for the power grid. The proportion of the total operating cost is increasing day by day, and the maintenance workload of relay protection equipment is increasing sharply (Zheng et al., 2022). In order to ensure the stable and reliable operation of the power grid in the case of such a large number of equipment and high equipment complexity, and at the same time control maintenance costs to reduce costs and reduce the workload of relay inspection, the maintenance strategy of power equipment has changed from regular maintenance in the past to state

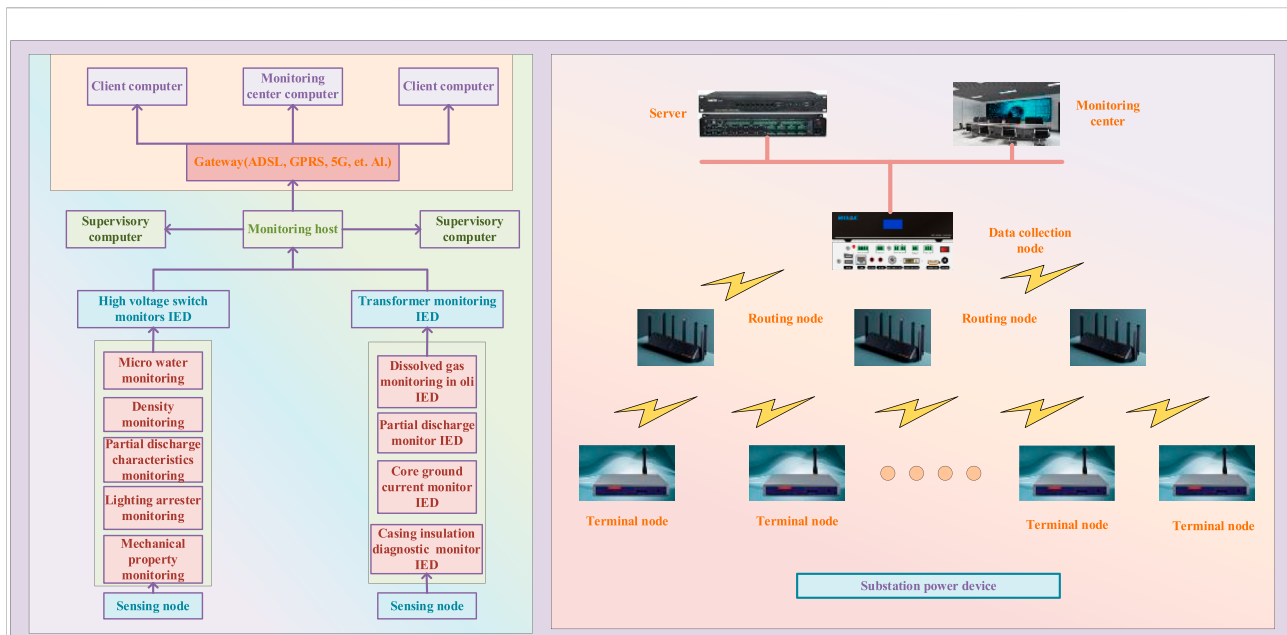


FIGURE 1

Overall layout diagram and hardware system structure of online monitoring system of smart substation.

Overhaul development. Both periodic maintenance and condition maintenance are preventive maintenance (Yang et al., 2021). The disadvantage of regular maintenance is that the maintenance cycle is relatively fixed, and the maintenance cannot be carried out in time according to the health status of the equipment, which is easy to cause problems such as insufficient maintenance and excessive maintenance. Condition-based maintenance is to obtain various state parameters of the equipment during operation through advanced state monitoring methods, identify the early signs of failures according to the actual working conditions of the equipment reflected by these state parameters, and make judgments on the fault location, fault severity, and development trend, to determine the optimal maintenance time of the equipment as a maintenance method (Shin et al., 2021).

With the development of the power industry around the world, the data of the power system has increased dramatically and has now reached the petabyte (PB) level. This means that the current power industry is entering the era of big data (Wang et al., 2021). Therefore, it is imperative to develop a maintenance strategy that can stably guarantee the operation of the power grid based on massive data. The maintenance of substation status is the basic work of power supply guarantee and power security, but it usually has great uncertainty and uncontrollability, so it puts forward higher requirements for the maintenance of substations. At present, there are many strategies applied to substation power grid maintenance, such as time-based maintenance strategy, corrective maintenance strategy, and condition-based

maintenance (CBM) strategy. Compared with the first two methods, CBM is widely used because it can reduce fault loss and prolong the service life of equipment (Xu et al., 2021).

At present, it is crucial to vigorously develop the key equipment and promote the construction of intelligent substation. Inspiringly, the intelligent inspection robot based on image vision and multi-sensor fusion has been applied to the status monitoring and intelligent maintenance of substations, and the cloud platform based on a large number of monitoring data has also been embedded in substations, called intelligent substations. Compared with the traditional substation, the intelligent substation currently under construction has a compact structure design, centralized secondary equipment, more reasonable layout, and small footprint. Intelligent substation is a high-level substation that adopts advanced intelligent equipment and can automatically complete basic functions such as information collection, measurement, control, protection, measurement, and monitoring with digitalization and standardization of information sharing of the whole station as the basic requirements. In particular, Figure 1 clearly shows the hardware structure and overall layout of the smart substation.

The intelligent substation evolved from the digital substation. After 10 years of development, the technology has become increasingly perfect. Compared with other links, intelligent substation has reached the conditions for large-scale promotion. The intelligent substation is mainly composed of equipment layer and system layer. The biggest difference between

the intelligent substation and the traditional substation is reflected in three aspects: the intelligence of primary equipment, the state of equipment maintenance, and the networking of secondary equipment.

After 2011, all newly-built substations will be constructed in accordance with the technical standards for intelligent substations, and the hub and central substation will be focused on intelligent transformation. As of the sixth batch of bidding in 2013, the bidding volume of smart substations has reached about 3600, which is basically in line with the planning expectation. However, the proportion of bidding for recent batches of smart substations has decreased compared with the previous period. As the pilot project of a new generation of intelligent substation is gradually put into operation, the proportion of intelligent substation bidding will continue to increase, and the construction progress will continue to accelerate.

Condition monitoring of smart substations can provide an important guarantee for maintenance and protection. In literature (Gao et al., 2022), a new state maintenance scheme is proposed and a big data architecture is designed for the state maintenance of power big data substation equipment to achieve the data collection and application integration functions of multi-source substation equipment. The intelligent detection system can obtain the operation data information of substation equipment, including substation, circuit breaker, and capacitor equipment. The intelligent monitoring system improves the traveling wave positioning ability by establishing a big data multi-classification fusion positioning model. Work (Xu, 2019) effectively monitors the intelligent operation and maintenance monitoring platform of the substation by deeply integrating the three modules of intelligent patrol monitoring, intelligent auxiliary equipment monitoring, and personnel management intelligent monitoring to achieve multi-source information fusion, which can be multi-dimensional, comprehensive, and visualized. Real-time monitoring of the operation status of main/auxiliary equipment and personnel safety of substations, to achieve comprehensive management and control of operation and maintenance equipment and personnel, and to improve operation and maintenance quality and efficiency. Reference (Fei et al., 2016) uses multi-source information fusion technology to automatically identify the operation status of high-voltage circuit breakers in substations. It has the characteristics of fast real-time response, strong anti-interference ability, and convenient maintenance. It is also convenient for operation management and monitoring, improves the safety performance of relay protection devices in power plants, and effectively ensures the stable operation of units. Reference (Pan and Zhang, 2013) introduces a substation auxiliary system management and control platform based on multi-sensor networks to meet the development requirements of intelligent substations. This method improves the reliability and stability of real-time monitoring of substation information, and

identifies and classifies fault targets. In addition, Table 1 summarizes the requirements for intelligent equipment of conventional 110–220 kV substations.

The rest of this paper is arranged as follows: The second part introduces the substation control technology and substation fault diagnosis technology based on neural network, the third part introduces the positioning function of substation patrol robot based on multi-source data fusion, the fourth part introduces the substation patrol robot based on multi-sensor fusion control technology, and the last part is the conclusion and prospects for future research.

Substation monitoring and control technology

Substation control technology based on machine vision

As a comprehensive technology including digital image processing and machine vision, substation monitoring technology has become an important part of ensuring the operation and maintenance of substations. The substation monitoring task is mainly realized through the Pan/Tilt/Zoom (PTZ) system, which is mainly composed of PTZ and testing equipment. A stable PTZ is the hardware prerequisite for obtaining high-quality information, and the real-time robust visual processing algorithm is the software guarantee for efficient detection. To realize the stable operation of the substation inspection work, the gimbal needs to meet the requirements of high control accuracy, good dynamic performance, and easy secondary development and can obtain equipment inspection information stably and quickly in the substation site with strong electricity and magnetism.

In addition to high-performance PTZ control technology and corresponding detection equipment, substation monitoring technology also requires stable and fast image detection algorithms. Visual detection technology is one of the key research directions at this stage, the essence of which is to detect the target position from the complex background environment, mark it with a rectangular frame, and perform coordinate acquisition and target classification. In particular, target detection techniques mainly include traditional processing methods and deep learning methods.

The double cascade parameter regression normalizes the target image, which realizes the registration of the instrument image and greatly reduces the false detection rate of the instrument (Fang, 2017). With the development of hardware equipment and the research of related algorithms, the target monitoring technology based on deep learning has greatly improved in terms of processing speed and monitoring accuracy, including Two-Stage and One-Stage (Duan et al., 2020; Liu and Meng, 2020; Lu et al., 2020). Two-Stage

TABLE 1 Functional requirements of intelligent equipment for 110–220 kV substations.

Serial No.	Device		Function
1	12 DOF anthropomorphic double arm mechanical module	Customized joints	Internal integrated reducer, low-voltage torque motor and servo driver, featuring high output torque, low deadweight, excellent electromagnetic compatibility and stable operation in high and low temperature environments. The Ethercat bus shall be used to realize high-speed communication, and the actual performance effect of high control refresh rate, high dynamic response, low delay, smooth and stable action shall be achieved
		Remote control bolt fastening device	It shall have large torque output characteristics and be compatible with wireless remote control. It is an end tool for live working and is used to develop a bolt fastening device for fittings
		Laser generator	It must have low power consumption characteristics to avoid damage to the equipment surface. It is the end tool for robot live working and is used to develop a foreign matter removal device
		Development of lightweight clamping mechanism	The clamping end used for developing the operating system can provide sufficient clamping force for holding hardware, wire segments, etc
		Electromagnetic protection materials	Used for withstand voltage shielding protection of live working system
2	Portable dual arm control system module	Environment intelligent monitoring and depth positioning system	It can provide an auxiliary perspective for the operating system to monitor the movement of mechanical devices in real time and avoid collision with the environment; It also provides distance judgment, which is convenient for operators to accurately locate and control
		Micro multi degree of freedom operator kit	It can be used to control multi degree of freedom mechanical devices, realize linkage control, and improve the control efficiency of the teleoperation system
		Fusion control base station	Support modular integration and development, and integrate relevant hardware and accessories as required, such as controller, display screen, touch screen, communication module, video module, power module, etc; The monitoring and motion control of remote devices can be completed through the base station module
		Mechanical and electrical system integration platform	The system level integrated platform shall have rich power interface, communication interface and mechanical hardware interface
		Battery and power management	The battery is used to provide the electrical energy required for the system work, while conducting safety management and protection for the charging and discharging of robots
3	Intelligent visual aid system module	Multi view image monitoring system	Multiple visual information can be provided for easy installation and integration; The main view angle is 1080P high-definition view angle, which is convenient for accurate observation and judgment of the operating environment and real-time detailed understanding of the operation; The auxiliary visual angle is used to be embedded into the end tools or operation arms, so as to facilitate close range observation of the details of the operation point and improve the operation accuracy
		Low delay communication	Point to point graph data integration module is adopted to ensure smooth interaction of data and images with low delay within the visual range of 200–300 meters
		Intelligent video server	It is used for real-time integration, editing and switching of multi view video images. It needs to support the input and output of multiple video formats, and has low latency features

includes two parts: candidate area generation, classification, and position trimming. The target monitoring accuracy is high but the monitoring speed is slow, which cannot meet the real-time requirements. One-Stage is mainly based on regression, does not require pre-generated candidate frames, has a simple structure, and has high monitoring speed. Since the introduction of convolutional neural networks, target monitoring algorithms have developed towards real-time performance and high

precision. In 2015, HeK et al. proposed the SPP-Net spatial pyramid pooling network based on the RCNN algorithm (Purkait et al., 2015), which broke through the limitation of image input size and improved the monitoring speed. In 2017, Girshick improved the R-CNN algorithm and proposed Fast-R-CNN (Shaoqing et al., 2015) and Faster-R-CNN (Redmon et al., 2016), which simplified the network structure and improved the efficiency of region matching respectively and greatly improved

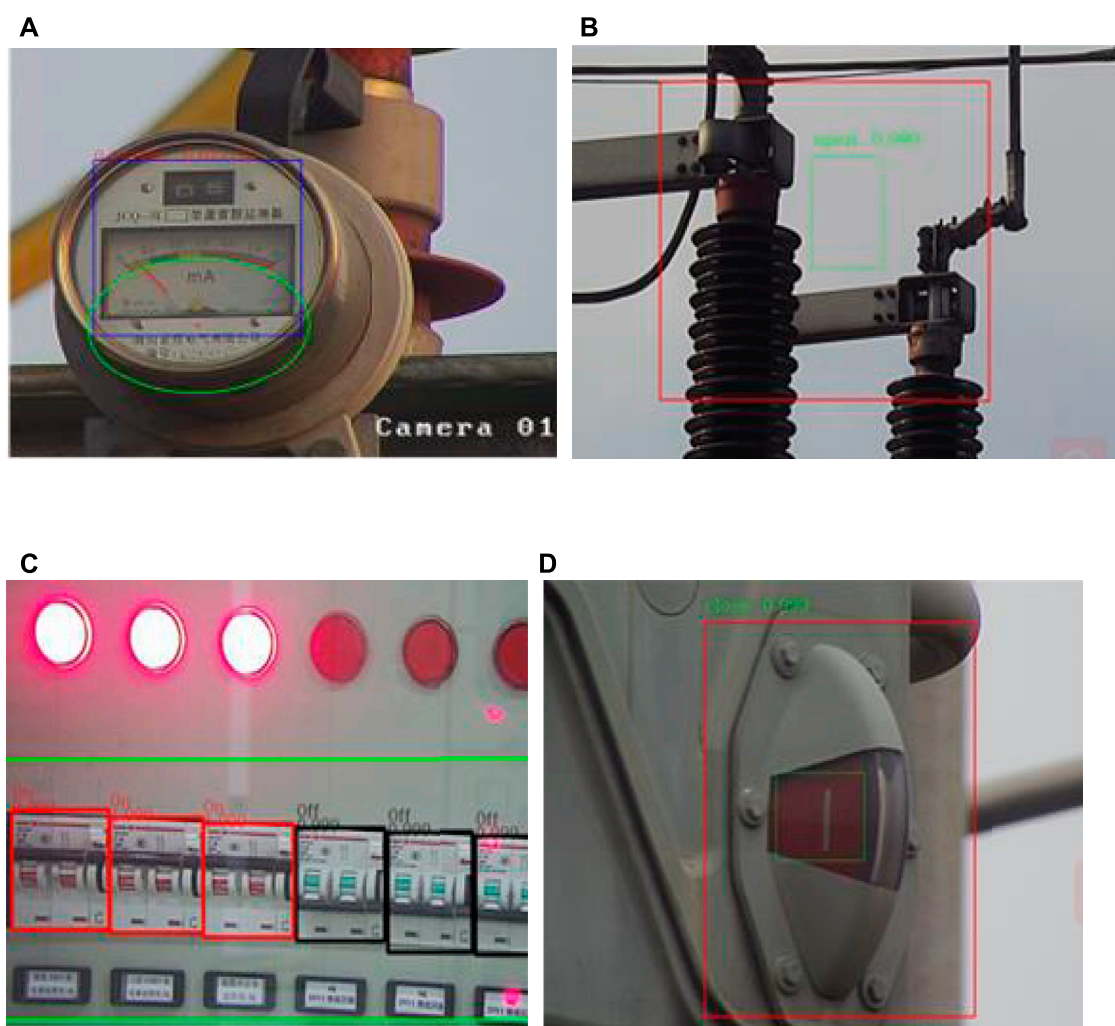


FIGURE 2

Fault identification of secondary equipment in 110–220 kV substation. (A) Arrester monitor pointer meter fault, (B) Auxiliary transformer bypass knife switch fault, (C) Air Switch of Emergency Lighting Inverter Panel fault, and (D) Opening-Closing Identification of Transformer fault.

the accuracy and speed, but still can not meet the needs of real-time monitoring. In 2017, Redmon et al. proposed YOLO9000, which realizes real-time monitoring of more than 9000 categories by combining classification and monitoring tasks (Beaudry and Poirier, 2012; Redmon and Farhadi, 2017). In 2018, Redmon et al. proposed the YOLOv3 algorithm (Redmon and Farhadi, 2018), which introduced a residual network structure, improved network performance, and improved monitoring accuracy and small target monitoring capabilities. In 2020, Alexey B combined various optimization strategies in the field of deep learning and proposed YOLOv4 based on the YOLOv3 framework (Bochkovskiy et al., 2020), which achieved efficient and accurate target monitoring. To sum up, substation monitoring mainly uses the PTZ equipped with visible light, infrared, and other multi-source visual devices to collect information about the

substation equipment and judge the operating status through the target monitoring and identification algorithm. Traditional monitoring algorithms have good monitoring performance in specific scenarios but have poor scalability and low intelligence, which cannot meet the equipment monitoring requirements in the complex environment of substations. The monitoring algorithm based on deep learning is trained through the data set, and the neural network automatically extracts the feature of the image target according to the label to complete the monitoring and identification work. However, it is not widely used in the field of substation equipment monitoring, and the general monitoring model is not yet clear. At present, substation monitoring mainly adopts traditional monitoring methods, and the method of deep learning cannot perform simultaneous monitoring of visible light and infrared, and the

real-time monitoring is poor, which needs further development.

Substation fault diagnosis technology based on parallel convolutional neural network

At present, the research on substation fault diagnosis is based on the fault mechanism model of HVDC transmission, and the other part is based on the method of line signal analysis, which does not simplify the circuit model. With the continuous development of artificial intelligence algorithms, artificial intelligence algorithms have been widely used in substation system fault diagnosis. In particular, the common fault types of 110–220 kV substation equipment are clearly listed in Figure 2. At present, both fault diagnosis methods based on mechanism model and signal analysis have the problem that the fault threshold is not easy to determine. Encouragingly, a substation fault diagnosis method with both rapidity and accuracy is proposed. Firstly, the amplitude and frequency characteristics of substation line fault signal waveform are analyzed, and the fault amplitude feature extraction method based on the amplitude change of signal waveform and the fault frequency feature extraction method based on wavelet packet analysis are studied to form a fault diagnosis method based on amplitude frequency characteristics. Secondly, a dual branch convolutional neural network with fault classification branch and fault location branch-parallel convolutional neural network is constructed, and a training method based on transfer learning is proposed.

As the current and voltage will fluctuate during the fault and finally stabilize to the new value, if the new stable value is different from the stable value during normal operation, the electrical quantity will change, so the fault type can be distinguished. The amplitude change characteristics before and after the new signal waveform are extracted as follows:

$$x(i) = [x_{T-1}, x_{T-1+\Delta T}, x_{T-1+2\Delta T}, \dots, x_{T-1+m\Delta T}, x_T, x_{T+\Delta T}, x_{T+2\Delta T}, \dots, x_{T+m\Delta T}] \quad (1)$$

where: $x(i)$ is the data after synthesis, T is the time of failure, ΔT is the time interval of the sampling point, $\Delta T = 10-4s$, $m = 19$, indicating that the number of sampling points $m+1$ is 20.

When the short circuit fault occurs in the substation system, the line current and voltage will produce high-frequency components, and the fault classification and location can be achieved by detecting these information. Eqs 2, 3 are wavelet packet decomposition algorithm and wavelet packet reconstruction algorithm respectively.

$$\begin{cases} d_{j,1,2n} = \sqrt{2} \sum_k h_{0,k-2l} d_{j+1,k,n} \\ d_{j,1,2n+1} = \sqrt{2} \sum_k h_{1,k-2l} d_{j+1,k,n} \end{cases} \quad (2)$$

$$d_{j+1,1,n} = \sum_k h_{0,k-2l} d_{j,1,2n} + h_{1,k-2l} d_{j,1,2n+1} \quad (3)$$

where $d_{j+1,k,n}$ is the results of wavelet packet decomposition of the previous layer, $d_{j,1,2n}$ and $d_{j,1,2n+1}$ are the wavelet packet decomposition results of the next level, j is the scale index, n is the frequency index, l is the location index, k is a variable, $h_{0,k-2l}$ and $h_{1,k-2l}$ are the $k-2l$ multi-resolution filter coefficients used for decomposition.

Substation fault diagnosis method based on improved genetic algorithm

Aiming at the problems of premature, low accuracy and slow convergence of traditional optimization algorithm in solving the analytical model of substation fault diagnosis, a substation fault identification method based on improved genetic algorithm was developed. First of all, in view of the shortcomings of traditional genetic algorithms such as slow convergence and insufficient global search ability due to the fixed crossover and mutation probability, the crossover probability related to evolutionary algebra and mutation probability related to individual fitness are designed, and the existing adaptive genetic algorithms are improved to improve the global search ability and convergence speed of the algorithm. Secondly, the analytic model of power grid fault identification is constructed according to the topology and protection configuration of the power grid. Finally, the improved genetic algorithm is applied to solve the above fault diagnosis model. The basic steps of traditional grid fault identification algorithm based on mathematical analytic model are as follows:

Step 1: generate fault hypothesis randomly.

$$S = [D C R] \quad (4)$$

where, D , C , R are respectively AC equipment, circuit breaker, and protected line vectors, and D is the corresponding equipment in fault or normal state, taking 0 or 1, C means that the corresponding circuit breaker is in the active or inactive state, and the value is 0 or 1, R means that the corresponding protection is in the active or inactive state, and the value is 0 or 1.

Step 2: describe the action logic of all circuit breakers and equipment protection of the power grid through strict mathematical equations, and calculate their expected values.

$$r_m^* = d_k \times \bar{r}_i \times \bar{r}_j + \sum_{d_l \in D(R_i)} \left(d_l \times \prod_{c_p \in C(R_m, D_l)} \bar{c}_p \right) \quad (5)$$

where $\bar{r}_i$ is the expected value of the i th backup protection equipment under the fault hypothesis, d_k is the fault hypothesis value of the protected equipment D_k , $\bar{r}_j$ is the fault hypothesis value of the j th near backup protection equipment.

The circuit breaker failure protection action logic is as follows:

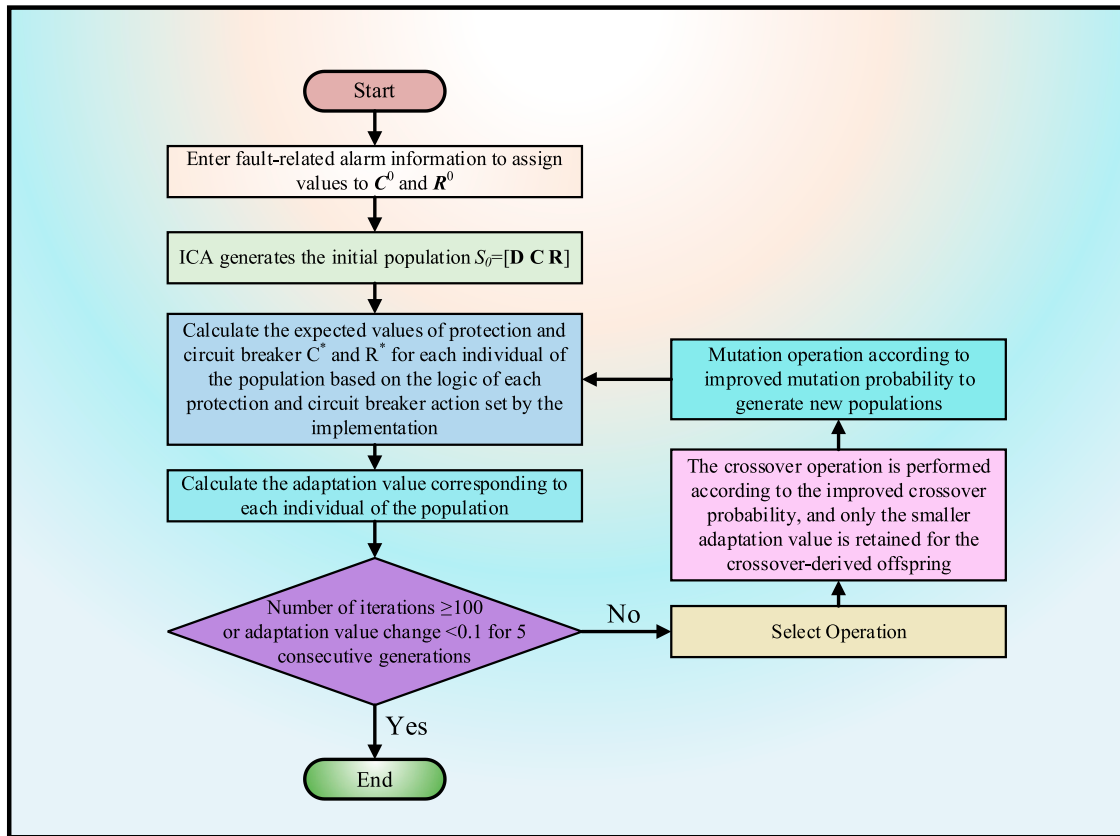


FIGURE 3

Flow chart of substation fault identification algorithm based on improved genetic algorithm.

$$f_{c_i}^* = \bar{c}_i \times \sum_{r_x \in R(c_i)} r_x \quad (6)$$

where $f_{c_i}^*$ is the breaker failure protection corresponding to the breaker c_i , and $R(c_i)$ is the set of all protections that can make the breaker c_i act.

The action logic of the circuit breaker is as follows:

$$\hat{c}_k^* = \sum_{r_i \in R(c_k)} r_i \quad (7)$$

where $\hat{c}_k^*$ is the expected value of circuit breaker c_k under the fault hypothesis state, and $R(c_k)$ is the protection set that can control the action of circuit breaker c_k .

Step 3, build the differentiation function between the actual state and the expected state of the circuit breaker and protection as the objective function.

$$E_{(S)} = \sum_{i=1}^{n_c} |c_i - c_i^a| + \sum_{j=1}^{n_r} |r_j - r_j^a| + \sum_{i=1}^{n_c} |c_i - \hat{c}_i^*| + \sum_{j=1}^{n_r} |r_j - r_j^*| + \alpha \left(\sum_{i=1}^{n_d} d_i \right) \quad (8)$$

where r_j^a and c_i^a They are respectively the action status of the j th protection and circuit breaker received by the dispatching center.

Step 4: Minimize and optimize the objective function by improving the genetic optimization algorithm, and the optimal solution is the fault identification result. The cross strategy is as follows:

$$P_c(t) = \begin{cases} P_{c,\max} \times e^{\left(-\frac{t}{T_{\text{Gen}}}\right) - \left(-\frac{t}{T_{\text{Gen}}}\right)^2} & \text{if } (m_{\text{tmp}} > P_{c,\min}) \\ P_{c,\min} & \text{else} \end{cases} \quad (9)$$

where m_{tmp} is an intermediate calculated variable, T_{Gen} is the preset maximum evolutionary algebra, t is the current evolutionary algebra, $P_{c,\min}$ and $P_{c,\max}$ are the preset minimum and maximum crossing probabilities respectively, $P_c(t)$ is the cross probability of the current population.

The mutation operation can maintain the diversity of the population and plays an important role in suppressing the premature of the algorithm, as follows:

$$P_m(t) = \begin{cases} 2 - \frac{|f_{\max} - f(X_i)|}{f_{\max}} & \text{if } (m_{\text{ump}} > P_{m-\min}) \\ P_{m-\min} & \text{else} \end{cases} \quad (10)$$

where $P_{m,\max}$ and $P_{m-\min}$ is the preset maximum and minimum probability of variation respectively, $f(X_i)$ is the fitness of individual X_i , $f_{\max}$ and $f_{\min}$ are the maximum and minimum fitness values of the population respectively, $P_m(t)$ is the variation probability of individual X_i in the t generation population.

In particular, Figure 3 is the flow chart of substation fault identification algorithm based on the above improved genetic algorithm.

Location technology of substation inspection robot based on multi-source fusion

Intelligent positioning of substation inspection robot

The traditional single inspection mode of substation is manual inspection. With the rapid development of economy, the scale of power system is expanding, and the requirements for system stability are increasing. The existing manual inspection mode is difficult to meet the above needs due to its high labor intensity, scattered inspection quality and severe interference from bad weather. It is difficult to make an objective, comprehensive and accurate judgment simply by relying on the sense and experience of patrol inspectors, laying hidden dangers for the safe operation of equipment. In recent years, a large number of substation patrol robots adapted to different environmental conditions have been developed, which has greatly promoted the application of intelligent patrol robots in substations, and promoted the improvement of substation patrol efficiency while saving manpower.

So far, the tracking technology of mobile robot mainly includes radar tracking, visual tracking and multi-sensor fusion tracking. Among them, radar tracking technology is the most widely used, but radar tracking is difficult to determine the type and geometric shape of the measured object, and it is difficult to achieve stable tracking in complex scenes, and the cost of radar components is high; Multi sensor fusion tracking is a relatively stable tracking method because it can obtain rich features, but it is difficult to register coordinates and has high cost; Compared with other technologies, visual tracking has a better recognition rate for the category of tracked objects, and the price of visual sensors is lower. However, this technology involves a large amount of computation, which limits its application in the field of mobile robots. In particular, work (LUO et al., 2021)

analyzed the current mainstream motion model generation candidate box method of patrol robots, and used adaptive Kalman filtering and least square method to process the robot's inertial sensor output, thus realizing the attitude estimation of the vehicle platform.

Early patrol robots only stayed in the experimental stage. In 2009, Canada developed a remote-controlled wheeled inspection robot using a handle, which can be equipped with RGB camera and infrared camera to inspect the power plant. In 2012, Massey University of New Zealand developed a robot control system and carried a vision acquisition device to monitor changes in the grid environment (Guo et al., 2009). At present, most of the existing inspection systems adopt the guidance and positioning method, and there are shortcomings in the laying process, such as excessive workload, low flexibility in path fixation, and inability to accurately anchor the specific position of the inspection robot (Salvucci et al., 2014). Therefore, studying accurate and robust navigation and positioning algorithms can lay a foundation for the stable operation of autonomous inspection robots (Zhang, 2019). Navigation and positioning is the key technology for patrol robot to realize intelligent patrol. Patrol robots generally use preset magnetic tracks and radio frequency identification (RFID) technology for positioning (Ju et al., 2020), but this method has low positioning accuracy and weak anti-interference ability. In recent years, although the sensor performance has been continuously improved, the positioning ability of a single sensor in harsh environments is still insufficient. For example, satellite navigation and positioning may fail in environments with large electromagnetic interference (Chi et al., 2021). The inertial navigation system is less affected by the environment, but the price of high-precision inertial measurement unit (IMU) is high, and low-precision IMU is easy to accumulate positioning errors (Dong et al., 2021). There are problems of unclear texture features and failure under high dynamic conditions when visual sensors are used for navigation and positioning (Budiyo, 2013), and there are problems of degradation when lidar sensors are used for positioning in open environments (Zhang et al., 2021). Document (Frosi and Matteucci, 2022) proposes a multi-sensor fusion algorithm based on Federated Kalman filtering (FKF) to integrate fault monitoring and information recovery algorithms and builds a smart grid platform based on AAA level game engine. A virtual sensor is constructed to verify the navigation and positioning algorithm of the smart grid inspection robot. In recent years, intelligent inspection robots developed around the world based on accurate positioning algorithms and advanced virtual sensors not only save manpower in substations but also improve maintenance efficiency. In particular, Figure 4 shows the mainstream substation monitoring robots around the world.

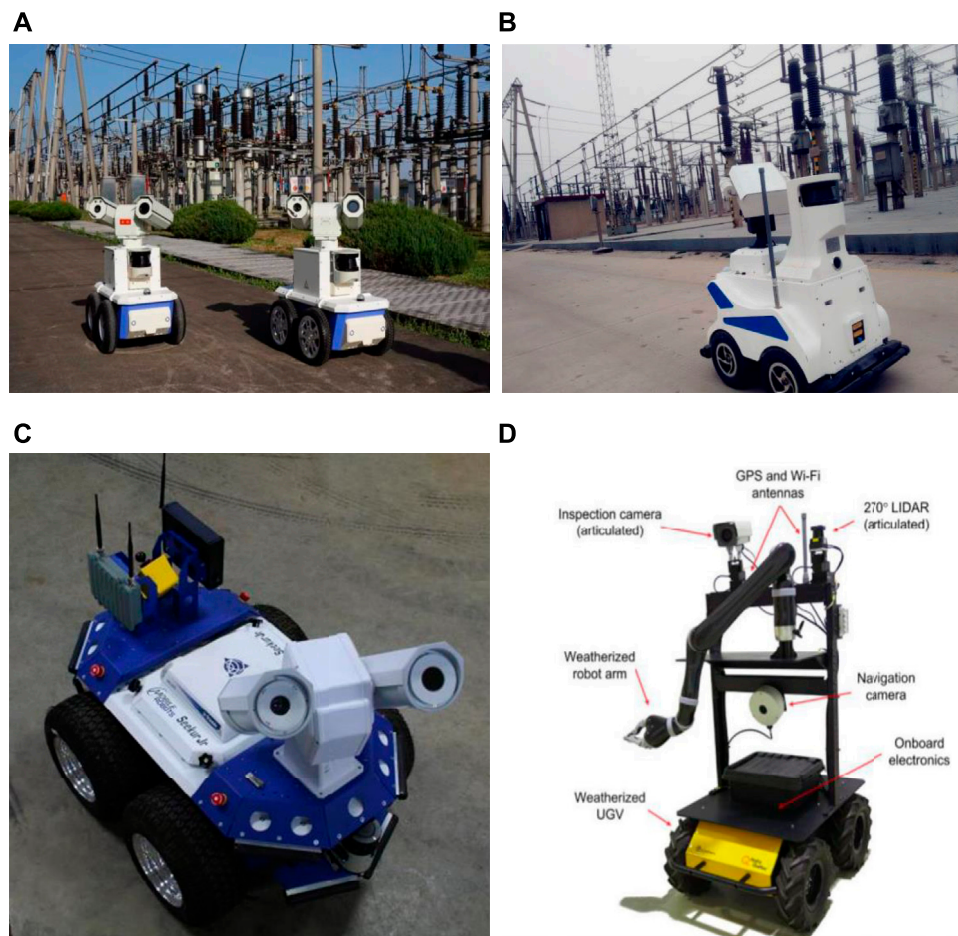


FIGURE 4

World mainstream substation intelligent inspection robot. (A) Hangzhou substation inspection robot in China, (B) Shandong Luneng intelligent maintenance robot in China, (C) Canadian substation monitoring robot, and (D) American electric power detection and operation robot.

Multi-robot joint inspection system based on multi-source data

A multi-robot system is a collection of robots that have dynamic and kinematic characteristics and can interact with other individuals. It can be predicted that more and more robots will be put into practical applications in the future, and the related research on multi-robot system will also have greater application value. The use of multi-robot linkage system in substations can show strong adaptability to complex environments. Its strong carrying capacity greatly shortens the working time and effectively improves production efficiency. In a multi-robot system, the completion of a task requires the participation of each robot, rather than completely depending on one robot. If the working environment changes or the system fails, the robot can re-plan the task to adapt to the environment through the central controller and its coordination system, so it has strong fault tolerance and robustness.

The inspection robot system is generally composed of the robot body, moving parts, background monitoring, control bus, and network, which involves the structural design of the robot and the intelligent control of the robot (Wen et al., 2022). According to the actual operation of the substation, this paper analyzes the existing technical level and functional requirements of the substation inspection robot, summarizes the information fusion technology of the inspection robot, and the dynamic planning of the inspection path into three points, as follows:

- a) Dynamic planning of patrol path based on multimodal environment information interactive perception: the calibration matching optimization algorithm between three-dimensional visual image sensing recognition and Radar Real-time ranging sensors is used to establish a multimodal environment information interactive perception fusion model, and then analyze the real-time reconstruction method of the non-structural complex

environment. The dynamic tracking compensation model of inspection path is constructed, and the autonomous path planning and obstacle avoidance control algorithm of substation inspection multi-robot system based on the unstructured complex environment reconstruction model is analyzed;

- b) Dynamic topology optimization and ad hoc networking of multi-robot mobile node network structure: MANET Routing Protocol mechanism, dynamic topology model, and real-time dynamic update of routing table of multi-robot system group in substation inspection are adopted. Combining the path dynamic change information of each node and the dynamic topology optimization of network nodes, the model construction of information interaction and fusion between the two is analyzed, and then the research on network topology change perception, network topology connection maintenance, and multi-channel access is carried out;
- c) Multi-robot complex system modeling: study the local interaction mechanism and coordination control algorithm between individual robots, and realize information perception and interaction between individual robots through controller design, sensor configuration, and multi-source information fusion. A multi-robot complex system modeling method based on the fusion of dynamic path planning, mobile network information transmission, multi-modal information interaction, and other technologies realizes the global coordinated control of multi-robot systems.

Power inspection robot based on multi-sensor fusion

Application of image vision in patrol robot

The vision localization algorithm (VLA) is usually composed of three core modules: pose tracking, local optimization, and loop closing. The pose tracking module realizes the calculation of the relative motion between camera frames. According to different types of cameras, VLA can be divided into pose tracking modules based on monocular cameras, binocular cameras, and RGBD cameras. Although these three different modules have different information processing methods, they all use the visual odometry (VO) algorithm in calculating the relative motion mode between image frames (Wen et al., 2022). Work (Caramuzza and Fraundorfer, 2011) proposed a parallel tracking and mapping method (PATM), the main idea of which is to simultaneously extract and track feature points and build a map. The tracking process tracks feature points, and the mapping process optimizes the map at the back end, this is the first time to propose the concept of visual slam front-end and back-end. In 2015, Raul Murartal in Spain proposed the

orb-slam algorithm based on feature points (Klein and Murray, 2007), which adds a loop closing thread for loop monitoring based on the PATM algorithm, which achieves good results in tracking and mapping and ensures the consistency of the global map and the robot's posture. At present, the visual slam method based on feature point method occupies the mainstream, which can work when the noise is large and the camera moves fast, but the map is sparse feature points.

In addition to using feature points, the direct method also provides another way of thinking, that is, when extracting feature points from an image, a large amount of useful information in the image is discarded, so the subsequent motion estimation does not use information other than feature points. RGBD cameras can directly obtain the depth information of the surrounding environment and reduce the calculation time of robot positioning and map building. They have been widely used and studied. Among them, the Kinect fusion algorithm developed by Microsoft has a significant impact on the tracking camera and map building (Mur-Artal et al., 2015), but the Kinect fusion method needs GPU acceleration to ensure real-time performance, and cannot ensure the accuracy of pose estimation when there are large differences in images.

Multi-sensor fusion positioning technology of inspection robot in substation

The multi-sensor fusion algorithm is a technology that fuses a variety of input sensor information to improve the output performance of the system. It performs positioning through the fusion of multiple sensors carried by the robot. The advantage is that it improves the robustness of the system and improves the accuracy of output data by combining the differences of sensors to complement each other.

Work (Newcombe et al., 2011) proposed a closed formula to predict the lidar frame line measurement, which makes feature correlation, residual error, and Graphical User Interface (GUI) display possible. With this formula, the extended Kalman filter (EKF) can be directly used to fuse the lidar and IMU data to estimate the full state of the inspection robot. When the Global Navigation Satellite Systems (GNSS) signal is masked, lidar can help reduce the uncertainty of state estimation in a certain direction. Literature (Lynen et al., 2013) proposed a general (MSF-EKF) framework, which can fuse the measurement data of different types of sensors and conduct sensor self-calibration. Work (Wu et al., 2017) integrates IMU odometer and vision, proposes a vision-aided navigation system (VINS) for wheeled robot positioning in view of the situation that there are unobservable motion constraints due to wheel slip during

robot rotation, and simulates the unobservable constraints of IMU in combination with the planar motion of the odometer, improving the accuracy of the positioning system. Because the system operation needs to initialize the zero deviation of acceleration and gravity, which is not easy to do on the mobile robot platform, the effect of this algorithm is not ideal (Cecerska-Hery et al., 2022).

Conclusion

As an important part of smart grid, smart substation is the information collection and command execution link of intelligent dispatching center, and the core link of power grid equipment operation and maintenance management. Intelligent diagnosis of equipment faults is of great significance for the construction of smart grids. In particular, condition-based maintenance is a reliable and economical substation maintenance method, and the correct and effective implementation of condition-based maintenance requires advanced condition monitoring technology and accurate condition monitoring data as support. This paper discusses the concept and monitoring objects of the condition monitoring of the secondary equipment of the smart substation; summarizes the research status of the information modeling of the secondary equipment of the smart substation and the analysis and processing methods of the condition monitoring data, and analyzes the various condition monitoring methods used in the smart substation. data sources, advantages and disadvantages, and their respective applicability. As the core of substation status assessment, the substation power inspection robot is based on image vision, its development has shortcomings such as accuracy, visual positioning, and moving speed. The current research obstacles in this field and the prospects for future research are mainly summarized as follows:

- a) The current research results of the visual positioning algorithm of inspection robots are rich, but the algorithm will be restricted by many environmental factors in the actual application process. For example, when the camera moves fast or the viewing angle changes greatly, the positioning effect of the algorithm is poor; when the light intensity is low, the visual localization algorithm does not work properly. These problems are still the difficulties that need to be solved in the research and application-oriented process of visual positioning algorithm;
- b) Various theoretical methods of fault diagnosis and fault early warning have been proposed in large numbers, however, potential engineers should develop corresponding products and software systems for substation condition monitoring, which has great research value for practical applications in smart substations;
- c) With the rise of big data and cloud computing, it is possible to consider building a cloud platform in substations or dispatch centers in the future to improve the analysis and processing capabilities of substation condition monitoring and other systems. With the construction of cloud platforms and the introduction of data stream mining, the Construct the primary and secondary joint substation condition monitoring system and subsequent advanced applications such as fault diagnosis system, fault early warning system, and condition maintenance decision support system based on it;
- d) Facing the application requirements of low cost, high precision, and high stability of the positioning system of the power inspection robot in the substation, future research should be dominated by the method of sensor fusion to obtain stable and accurate positioning results and efficient and stable operation of the inspection robot;
- e) Advanced artificial intelligence algorithms should be widely used in the field of identification and positioning of patrol robots. Patrol inspection data should be compared and trend analyzed to timely find potential accidents and fault precursors in power grid operation, to effectively reduce the labor intensity of operation and maintenance personnel, and provide all-round security guarantee for substations;
- f) To solve the problem that it is difficult to reliably model the target and background with a single feature in the moving scene of the substation patrol robot, it can be improved from the perspective of feature selection, and to solve the problem of high computing cost of the depth learning method, it can be improved from the perspective of network structure optimization. In order to solve the problems of less prior information of tracked objects and easy deformation of objects in mobile robot tracking, research can be carried out from the perspective of model updating strategy, and a better model updating mechanism can be developed to improve the speed and accuracy of the algorithm.

Author contributions

WZ, AC, and MF: writing the original draft and editing, LY, KC, and XG: discussion of the topic.

Acknowledgments

The authors gratefully acknowledge the support of the first batch (supplementary) science and technology projects of Yunnan Power Grid Co., Ltd. in 2022-Research and Application of the Key Technology of Live Disconnection of the Drain Wire of Disconnecter in 110–220 kV Substation

Bus Side under Complex Environment (059400KK52220003).

Conflicts of interest

WZ, AC, MF, LY, KC, and XG were employed by transmission branch of Yunnan Power Grid Co., Ltd.

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Nomenclature

CBM condition-based maintenance

EKF extended Kalman filter

FKF Federated Kalman filtering

GNSS Global Navigation Satellite Systems

GUI Graphical User Interface

IMU inertial measurement unit

MSF-EKF multi-sensor extended Kalman filter

PATM parallel tracking and mapping method

PB petabyte

PTZ Pan/Tilt/Zoom

RFID radio frequency identification

VINS vision-aided navigation system

VLA vision localization algorithm

VO visual odometry



OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 14 September 2022

ACCEPTED 30 September 2022

PUBLISHED 09 January 2023

CITATION

Ai X, Li S and Xu H (2023), Wind speed
prediction model using ensemble
empirical mode decomposition, least
squares support vector machine and
long short-term memory.
Front. Energy Res. 10:1043867.
doi: 10.3389/fenrg.2022.1043867

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Wind speed prediction model using ensemble empirical mode decomposition, least squares support vector machine and long short-term memory

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Due to the randomness and intermittency of wind, accurate and reliable wind speed prediction is of great importance to the safe and stable operation of power grid. In this paper, a novel hybrid wind speed forecasting model based on EEMD (Ensemble Empirical Mode Decomposition), LSSVM (Least Squares Support Vector Machine), and LSTM (Long Short-Term Memory) is proposed, aiming at enhancing the forecasting accuracy of wind speed. The original data series is firstly processed by EEMD and SE into a series of components with different frequencies. Subsequently, a combined mechanism composed of LSSVM and LSTM is presented to train and predict the high-frequency and low-frequency sequences, respectively. Finally, the predicted values of all the data sequences are superimposed to obtain the ultimate wind speed forecasting results. In order to respectively illustrate the superiority of data feature processing and combined prediction mechanism in the proposed model, two experiments are performed on the two wind speed datasets. In accordance with the four performance metrics of the forecasting results, the EEMD-LSTM-LSSVM model obtains a higher accuracy in wind speed prediction task.

KEYWORDS

wind speed forecasting, long short-term memory, least squares support vector machine, ensemble empirical mode decomposition, sample entropy

1 Introduction

In recent years, with the improvement of people's environmental awareness, renewable energy resources such as wind energy have attracted more and more attention worldwide. Unlike traditional fossil fuels that results in environmental pollution and global warming, wind energy, as a clean and pollution-free form of practical renewable energy, has become a research hotspot around the world (Huang et al., 2022). According to a wind report published by the Global Wind Energy Council, more than 90 GW of new wind power capacity was installed in 2020, raising the total installed capacity to 743 GW, up 14.3% from the previous year. In particular, China's total

installed capacity accounted for 38.5% of global wind power capacity with the largest proportion (Wang et al., 2021). Despite such surprising growth, the randomness, uncertainty and intermittency of wind greatly affect the stable operation of large-scale power grid-integrated systems (Sun et al., 2022). An effective way to address this issue is to accurately predict wind speed.

Recently, a lot of prediction methods have been proposed, which are roughly divided into two categories, namely physical methods and statistical methods (Liu et al., 2018a). The physical methods, such as numerical weather prediction (NWP) and weather researcher forecasting (WRF), approximately simulate future wind speed using meteorological factors (atmospheric pressure, temperature, density, etc.) for comprehensive analysis (Xiao et al., 2018). One advantage of physical methods is to predict wind speed directly from real-time data, which, however, requires a large amount of physical information with high precision, thus leading to significant economic cost.

As the data science increasingly develops, statistical methods including conventional statistical models and artificial intelligence (AI)-based statistical models, have been widely regarded for time series forecasting (Hao and Tian, 2019). This type of method can effectively mine historical information and explain signal features (Aslam and Albassam, 2022). The conventional statistical models, like autoregressive (AR) (Poggi et al., 2003) and AR-integrated moving average (ARIMA) (Yunus et al., 2015), can predict wind speed on the basis of historical data and characterize linear fluctuation trend, but fail to adequately capture nonlinear features within wind speed data. To avoid nonlinearity, the AI-based statistical models have emerged continuously, including back-propagation neural network (BPNN) (Sun and Wang, 2018), support vector machine (SVM) (Liu et al., 2016) and least squares support vector machine (LSSVM) (Yuan et al., 2015). Among them, the structures of neural network are difficult to determine and the calculation process of traditional SVM is relatively complicated. In contrast, as an improved effective technology, LSSVM, which requires fewer parameters and owns higher convergence speed, has been widely utilized for predicting wind speed. For example, Du et al. (2018) proposed a novel robust hybrid system using LSSVM for electrical power system forecasting, and verified the satisfactory accuracy of the proposed hybrid model. The previous examples demonstrated that traditional AI-based methods are capable of extracting nonlinear and uncertain features of wind speed data but more suitable for handling series forecasting issues with low complexity.

To the best of our knowledge, the volatility and nonlinearity of wind speed series are attributed to the interference of various natural factors, thus shallow AI-based prediction models can hardly learn the sophisticated features from massive historical data, especially for the high-frequency sequence characterized by randomness and short-term dependency. Because of the hierarchical and distributed feature representations, deep

learning (DL) network possesses strong capability to predict high-frequency sequence and robustness to parameters (Hu and Chen, 2018). Deep learning methods including long short-term memory (LSTM) (Shahid et al., 2021), convolutional neural network (CNN) (Yu et al., 2020), deep belief network (DBN) (Wang et al., 2016a), and gated recurrent unit (GRU) (Li et al., 2022) have drawn much attention recently. Liu et al. (2018b) proposed a deep learning framework based on LSTM neural network for one-step forecasting of wind speed. In terms of multi-step forecasting, Moreno et al. (2020) forecast each component resulting from a two-stage signal decomposition strategy by employing LSTM network. As described earlier, DL-based LSTM neural network has been extensively used to forecast highly complex wind speed series due to its remarkable ability of learning and remembering both short and long-term features.

In recent years, it is widely recognized that hybrid or ensemble models based on signal processing have achieved admirable results in wind speed forecasting. Signal processing, namely data decomposition and reconstruction, is regarded as a key step to enhance the forecasting performance and efficiency of time series. Among these decomposition strategies, ensemble empirical mode decomposition (EEMD), as a modified version of empirical mode decomposition (EMD), can effectively avoid mode aliasing by adding normally distributed white noise into raw signal. Wang et al. (2016b) have proved that the prediction accuracy for wind speed can be improved by using EEMD.

Summarily, the aforementioned filter methods can decompose an original data signal into multiple subseries with various frequency-scales, making them more stationary and regular for further prediction. Nevertheless, the computation time of signal processing-based models will be inevitably prolonged with the increase in the number of components. In order to balance forecasting accuracy and economical cost, entropy has been developed to calculate the time complexity of data series as well as aggregate the decomposed components.

Due to the non-stationary nature of wind, wind data series contains complex characteristic information. Although filter methods can effectively reduce the volatility of wind series to some extent, components with different frequencies have different characteristics that can be matched with different learning mechanism to adequately exert the advantages of different models. Chen et al. (2022) used two different predictors, namely LSTM and improved BPNN, to respectively predict sequences with high-complexity and low-complexity. Hu and Chen (2018) similarly proposed a LSTM-based nonlinear combined mechanism to avoid the influence of single model on the prediction results. Additionally, Fu et al. (2020) proposed a composite prediction method containing KELM and ConvLSTM in the light for the frequency scales of each component to further improve the generalization capability and robustness of a single model. When it comes to data sequences mixed with different frequency scales, combining the strengths of different prediction models will be a

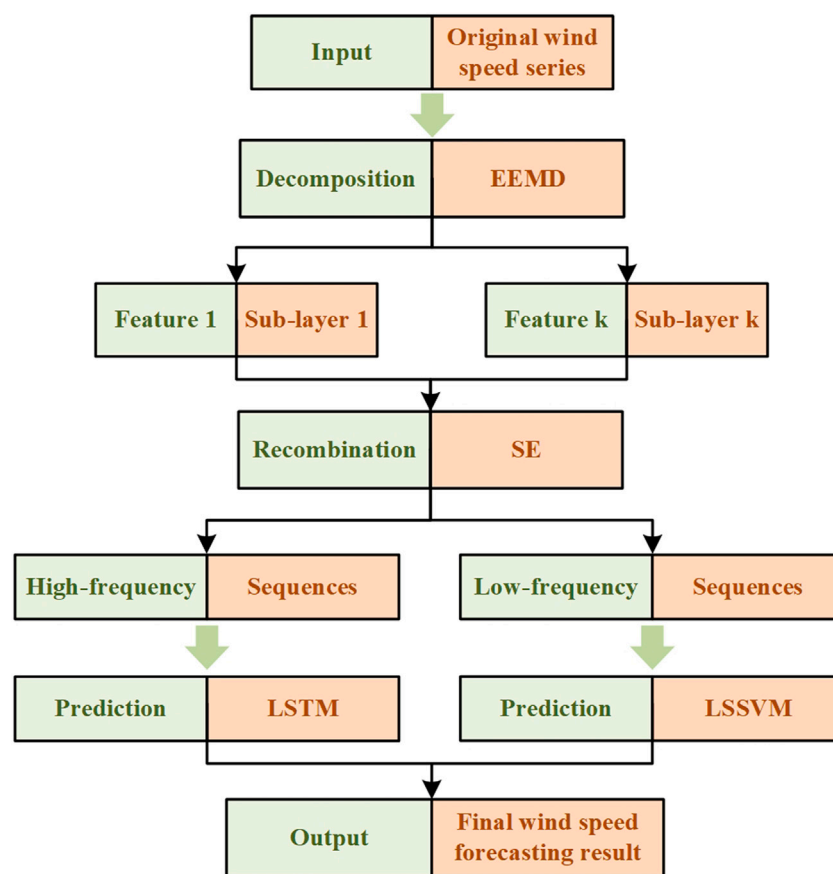


FIGURE 1
Flowchart of the EEMD-LSTM-LSSVM model.

promising way to achieve accurate prediction results. Thus, this paper integrates signal analysis method and different predictors together for wind speed forecasting.

The main contributions in this paper are described as follows:

- A hybrid wind speed prediction model (EEMD-LSTM-LSSVM) is proposed to overcome the disadvantage of single prediction model by using EEMD, LSSVM, and LSTM network.
- The original data signal is decomposed into a series of sub-layers applying EEMD to extract the fluctuation features, and then reconstructed into several frequency scales of sequences using sample entropy (SE) to reduce workload.
- To avoid the influence of single method on forecasting ability, a combined mechanism containing LSTM and LSSVM is developed. The high-frequency sequences are predicted by fitting into LSTM network, while remaining sequences (low-frequency ones) are predicted by LSSVM.
- The superiority of the developed combined mechanism is verified on two wind speed datasets by comparing single

benchmark models and hybrid benchmark models based on BPNN, SVR, LSSVM, LSTM, and persistence model.

The remainder of this paper is arranged as follows: [Section 2](#) describes hybrid EEMD-LSTM-LSSVM model. In [Section 3](#), two experiments are conducted on two datasets and comparative analysis is performed. [Section 4](#) summarizes the conclusions and future research directions.

2 The EEMD-LSTM-LSSVM model

2.1 Framework of EEMD-LSTM-LSSVM model

The flow chart of the EEMD-LSTM-LSSVM model is presented in [Figure 1](#), which is generally described as follow:

- The EEMD is firstly employed to decompose the original signal into different sub-layers with different complex

feature information, also known as intrinsic mode functions (IMFs).

- (2) To reduce the number of IMFs to be predicted, SE is used to calculate the sample entropy value of every sub-layer, and reconstruct it into several new high-frequency and low-frequency components.
- (3) Aiming at all components with different frequencies, LSTM network is adopted to forecast the high-frequency sequences, while LSSVM model to forecast low-frequency sequences.
- (4) The final forecasting results of original data series are obtained by superimposing the predicted values of all the sequences. In order to measure the prediction accuracy of all the experimental models, four performance evaluation metrics are adopted in this paper.

2.2 Ensemble empirical mode decomposition

As an effective signal-processing tool, EMD, proposed by Huang et al. (1998), has been widely implemented for time-frequency analysis. Its role is to adaptively decompose the original nonstationary sequence into multiple subsequences with different frequencies, also known as intrinsic mode functions (IMFs). However, the disadvantages of separation and intermittency results in the poor performance of separating similar frequency components and thus modal aliasing. To tackle this drawback and enhance the signal-processing ability of EMD, a modified version EEMD was introduced by Huang and Wu (2009) to effectively ameliorate mode aliasing by adding normally distributed white noise into raw non-stationary wind series. Great progress has been made on EEMD, an improvement and optimization of EMD in operation speed and computational efficient. In this paper, the difficulty in accurate forecasting of wind speed is attributed to its nonlinearity and non-stationarity. Accordingly, EEMD is employed to decompose raw wind speed series to make prediction less difficult and serve for subsequent aggregation.

2.3 LSTM-LSSVM-based combined mechanism

The data sequences of different frequencies obtained from EEMD and SE contain different characteristic information, which can be substituted into different learning mechanisms to avoid the influence of a single model on the forecasting performance. Consequently, hybrid models based on the combined mechanism are generally superior to single prediction models. Here, LSTM and LSSVM models are used to respectively predict high-frequency and low-frequency sequences. In order to validate the feasibility of the combined mechanism, two kinds of above sequences are selected from the

TABLE 1 Comparison of two prediction models using different sequences.

	Model	MAE	MSE	RMSE	MAPE
High-frequency	LSTM	0.1976	0.0686	0.2619	0.5662
	LSSVM	0.2403	0.0996	0.3156	0.6216
Low-frequency	LSTM	0.0090	0.00017	0.0132	0.0009
	LSSVM	0.0056	0.00004	0.0066	0.0005

following datasets for comparative experiment. The comparison results are shown in Table 1.

It can be intuitively observed from Table 1 that LSTM outperforms LSSVM in the processing of sequences with higher frequency, but inferior to LSSVM in the processing of sequence with lower frequency. Thus, this paper puts forward the combined mechanism of LSTM-LSSVM, whose strength is to avoid the preference of single predictor to data feature processing and minimize the prediction error (Hu and Chen, 2018).

3 Experiments and analysis

In this section, the two used wind speed datasets are firstly described in Section 3.1, and then the forecasting accuracy of the EEMD-LSTM-LSSVM model is to be demonstrated on two comparative experiments using two datasets. All the employed models are performed in MATLAB R2018a on a server equipped with 2.31 GHz CPU and 16 GB RAM.

3.1 Data description

The original data series of wind speed used in this paper are available on websites (<https://www.kaggle.com/datasets>). To validate the effectiveness of the proposed model, two groups of wind speed datasets containing 1,000 data points were selected as the experiment data. Taking five consecutive wind speed data as the input of models, each group of 1,000 data was constructed into a data matrix of 995 rows and five columns, in which the first 80% was used as training sets and the remaining 20% as test sets, as shown in Figures 2, 3. The statistics of two wind data series are given in Table 2.

3.2 Experimental setting

In order to further verify the superiority of the proposed model, two groups of comparative models were divided into single benchmark models and hybrid benchmark models for different purposes. Five single benchmark models, namely persistence model, BPNN model, support vector regression

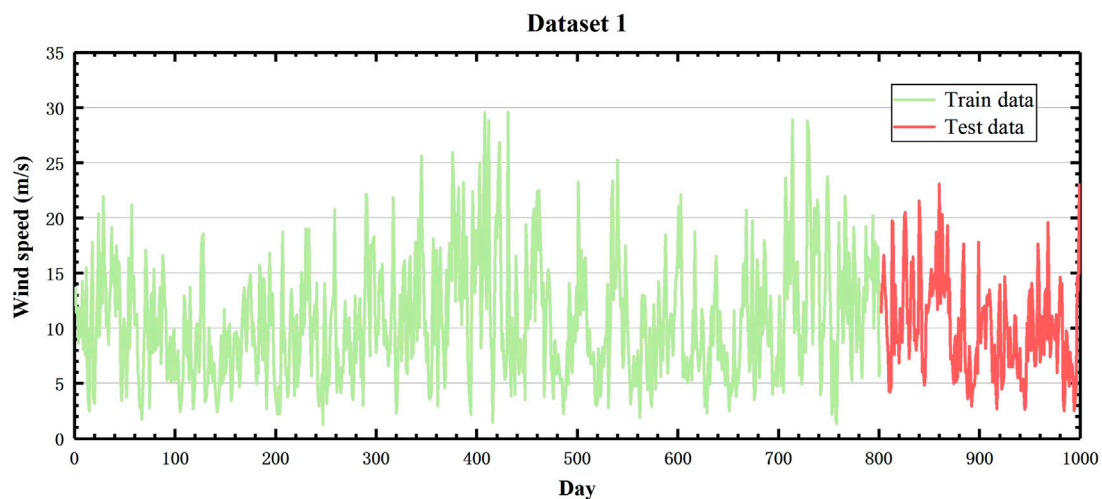


FIGURE 2
Original wind speed dataset 1.

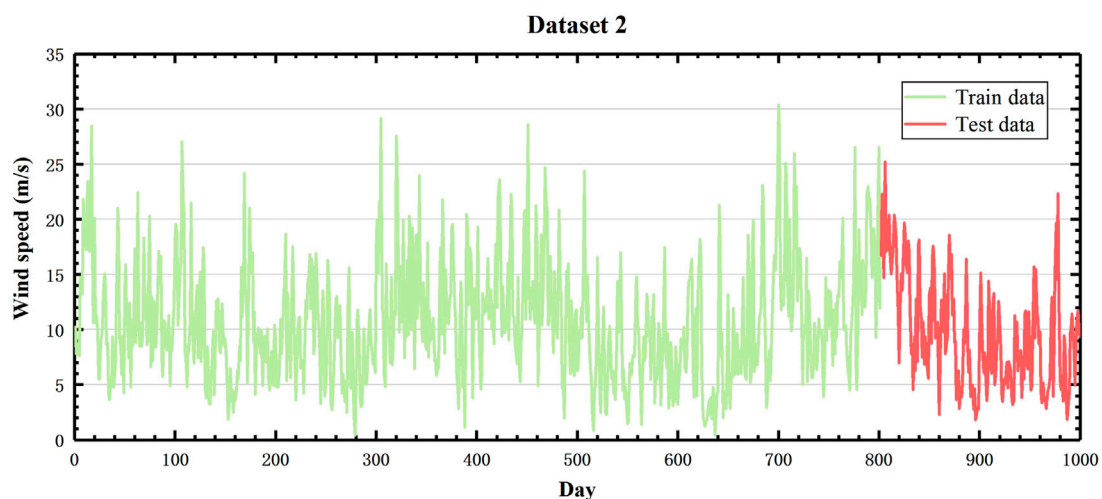


FIGURE 3
Original wind speed dataset 2.

(SVR), LSSVM, and LSTM model, were used for the first experiment, aiming to illustrate the superior capability of data preprocessing to improve the forecasting accuracy of wind speed by comparing the model after preprocessing with other five single models. The role of the second group of models was to investigate the impact of such combined mechanism on the forecasting performance of wind speed by comparing the multi-predictor model with single predictor model. Four benchmark prediction models, EEMD-BPNN, EEMD-SVR, EEMD-LSSVM, and EEMD-LSTM, were used for the second experiment.

According to Peng et al. (2020) and Moreno et al. (2020), the key parameters of the above employed models are set by the trials, as listed in Table 3. Specifically, the two parameters for EEMD algorithm, namely Nstd and NE, are set as 0.2 and 100 respectively, according to Sun and Wang (2018). For BPNN model, the number of hidden neurons is 10, the maximum training number is 2,000, and the target training error is 0.005, according to Peng et al. (2020) and Cui et al. (2021). In terms of LSSVM, one key parameter r is set to 200 and another parameter δ to 12 by the trials (Yuan et al., 2015). The

TABLE 2 The statistical information of two data sets.

Data set	Samples	Statistical information (m/s)			
		Max	Min	Mean	Standard deviation
Data set 1	Entire data (995)	29.58	1.25	10.51	5.23
	Train data (796)	29.58	1.25	10.61	5.40
	Test data (199)	23.09	2.54	10.16	4.52
Data set 2	Entire data (995)	30.37	0.42	10.55	5.35
	Train data (796)	30.37	0.42	10.76	5.41
	Test data (199)	26.54	1.79	9.88	5.18

TABLE 3 Key parameter setting for each model.

Model	Parameter	Value
EEMD	Nstd	0.2
	NE	100
BPNN	Number of hidden neurons	10
	Maximum of epochs	2000
	Goal error of training	0.005
LSSVM	Regularization parameter r	200
	Kernel bandwidth δ	12
LSTM	Optimizer	Adam
	Number of hidden units	200
	Initial learn rate	0.009
	Learn rate drop period	125
	Learn rate drop factor	0.2
	Maximum of epochs	500

TABLE 4 EEMD subsequences and recombination.

	IMFs	SE value	Result	New subs
Data set 1	IMF1	1.8208	IMF1	Sub1
	IMF2	1.0934	IMF2	Sub2
	IMF3	0.6482	IMF3&IMF4&IMF5	Sub3
	IMF4	0.5490		
	IMF5	0.4199		
	IMF6	0.1718	IMF6	Sub4
	IMF7	0.0379	IMF7&IMF8&IMF9	Sub5
	IMF8	0.0345		
	IMF9	0.0120		
Data set 2	IMF1	1.7741	IMF1	Sub1
	IMF2	1.2256	IMF2	Sub2
	IMF3	0.6511	IMF3&IMF4&IMF5	Sub3
	IMF4	0.5450		
	IMF5	0.4074		
	IMF6	0.1825	IMF6	Sub4
	IMF7	0.0446	IMF7&IMF8&IMF9	Sub5
	IMF8	0.0339		
	IMF9	0.0049		

parameters for SVR model are also set by the trials. One hidden layer with 200 neurons is adopted for LSTM model, with 500 epochs at most, according to [Moreno et al. \(2020\)](#). In addition, four typical performance metrics, namely mean absolute error (MAE), root mean square error (RMSE), mean absolute percent error (MAPE) and coefficient of determination (R^2), are used to measure the prediction accuracy of the employed models in this paper. The equations for these metrics are given as:

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}$$

where N is the number of test samples, $\bar{y}$ is the mean value of test samples, and y_i and $\hat{y}_i$ are the i th actual value and predicted value respectively. Note that the greater the value of R^2 is, the better the forecasting performance is.

3.3 Data decomposition and reconstruction

As an adaptive signal analysis method, EEMD was firstly used to decompose the original signal into nine sub-layers including eight IMFs and one residual, and then SE was used to calculate the sample entropy values of each IMF component. The greater the SE value is, the higher frequency the time series

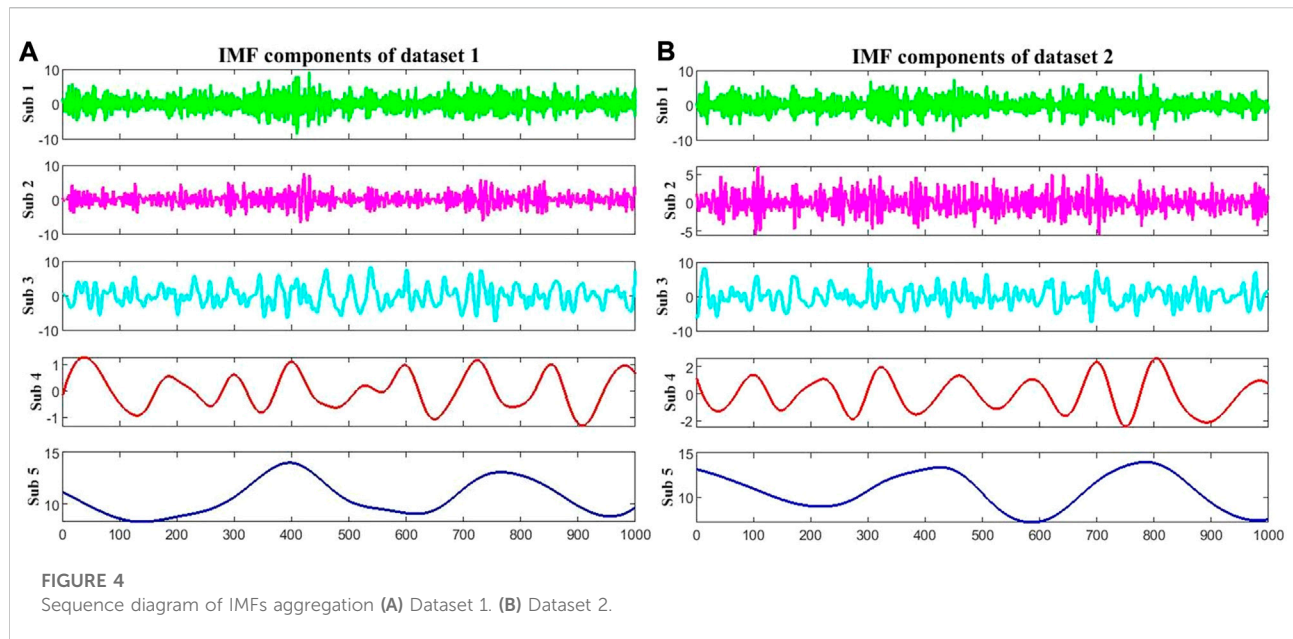


TABLE 5 Performance metrics of six models on experiment I.

	Dataset 1				Dataset 2			
	MAE	RMSE	MAPE	R^2	MAE	RMSE	MAPE	R^2
Persistence	3.1536	4.2552	0.3468	0.0991	3.0819	3.8675	0.3825	0.4016
BPNN	2.9501	3.7575	0.3669	0.2975	3.0079	3.6693	0.4447	0.4613
SVR	2.9203	3.7602	0.3403	0.2965	2.9071	3.6102	0.4064	0.4786
LSSVM	2.8843	3.7399	0.3459	0.3040	2.9690	3.6391	0.4324	0.4702
LSTM	2.8844	3.6851	0.3561	0.3243	2.8885	3.5409	0.4183	0.4984
Proposed	0.9775	1.2712	0.1127	0.9196	0.8720	1.0921	0.1132	0.9523

The bold values mean the best results among all the comparative models.

has. In order to reduce workload and avoid excessive decomposition, nine sub-layers were reconstructed into two high-frequency and three low-frequency sequences according to similar SE values, as presented in Table 4 and Figure 4.

3.4 Result analysis

In this section, the performance of EEMD-LSTM-LSSVM model is to be proved by comparing with single benchmark models and hybrid benchmark models respectively using two wind speed datasets.

3.4.1 Comparative experiment I: EEMD-LSTM-LSSVM and single benchmark models

In order to demonstrate the impact of EEMD-based preprocessing method in the proposed hybrid model, single

persistence model, BPNN, SVR, LSSVM, and LSTM models are employed for comparison. The prediction results of the six models applied on two datasets are presented in Table 5, where the optimal result is highlighted in bold. Figure 5 shows the wind speeds predicted by the six models. Figure 6 further displays the line comparison between the actual data and the predicted data obtained by EEMD-LSTM-LSSVM for two datasets.

It can be clearly observed from Table 5 and Figures 5, 6 that the EEMD-LSTM-LSSVM model proposed in this paper is obviously superior to five single benchmark models, with the MAE, RMSE, MAPE, and R^2 values of 0.9775, 1.2712, 0.1127, and 0.9196 for dataset 1 and with the MAE, RMSE, MAPE, and R^2 values of 0.8720, 1.0921, 0.1132, and 0.9523 for dataset 2, respectively, which suggests that the hybrid prediction model based on data preprocessing is more reliable to extract different characteristic information. Among the five compared models, LSTM model performs the best especially for dataset 2, which

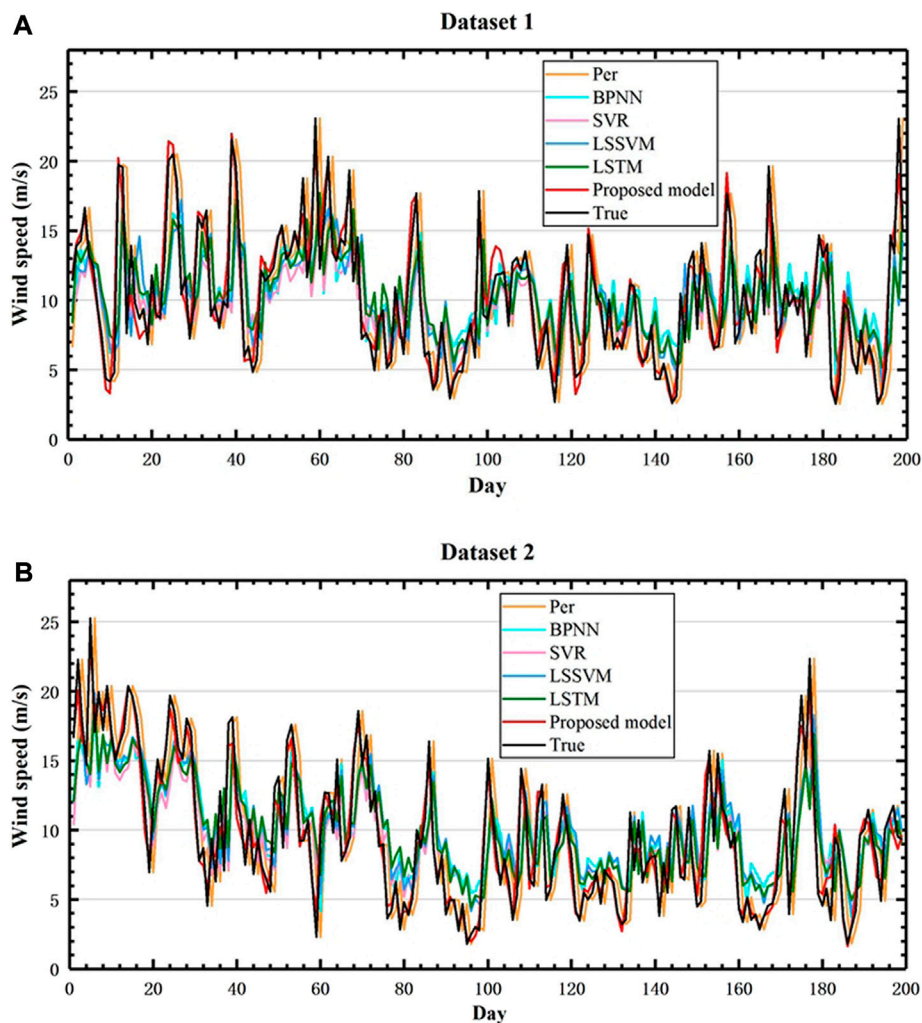


FIGURE 5
The line chart of forecasting results on experiment I (A) Dataset 1. (B) Dataset 2.

indicates that DL-based prediction methods outperform traditional models.

3.4.2 Comparative experiment II: EEMD-LSTM-LSSVM and hybrid benchmark models

The second experiment is devoted to verify the superiority of combined mechanism of two predictors to EEMD-BPNN, EEMD-SVR, EEMD-LSSVM, and EEMD-LSTM. Table 6 shows the performance metrics of five hybrid models, and Figure 7 further displays the 3D bar graphs of forecasting results using two datasets respectively. In addition, Figure 8 shows the wind speeds forecast by the five models.

As can be clearly seen from Table 6 and Figures 7, 8, whether dataset 1 or dataset 2, the EEMD-LSTM-LSSVM model favorably ranks among the four hybrid compared

models, which demonstrates the superiority of combined mechanism for two predictors to improve the accuracy of forecasting results. Additionally, the employed hybrid models on experiment II have obvious advantages in four performance metrics over the single benchmark models on experiment I. Thus, it can be reasonably concluded that data preprocessing strategy has obvious influence on the forecasting performance.

3.4.3 Summary of experiment I-II

Based on the results of experiment I-II, the conclusions can be drawn as follows:

- (1) The combined EEMD-LSTM-LSSVM model based on EEMD, LSSVM, and LSTM network not only is capable to more effectively forecast wind speed than other

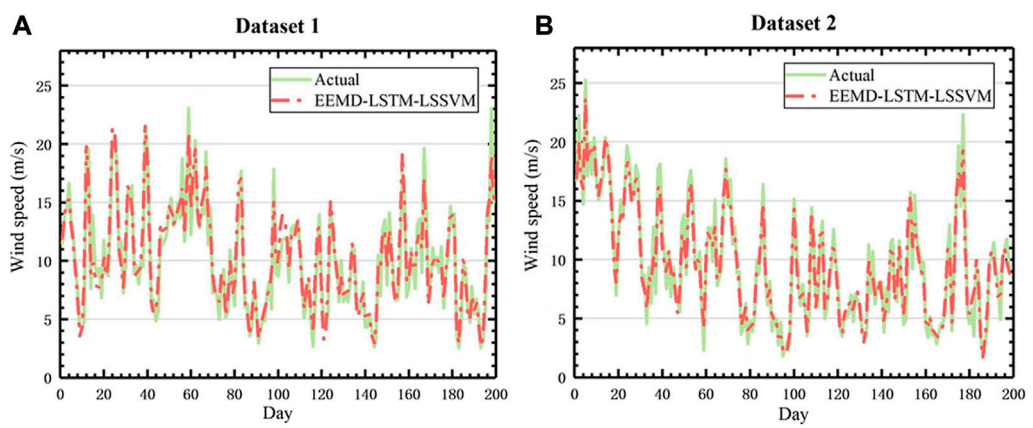


FIGURE 6
Predicted results obtained by EEMD-LSTM-LSSVM (A) Dataset 1. (B) Dataset 2.

TABLE 6 Performance metrics of five models on experiment II.

	Dataset 1				Dataset 2			
	MAE	RMSE	MAPE	R^2	MAE	RMSE	MAPE	R^2
EEMD-BPNN	1.4805	1.8815	0.1746	0.8239	1.2553	1.5806	0.1819	0.9000
EEMD-SVR	1.6078	1.9726	0.1967	0.8064	0.9053	1.1240	0.1243	0.9495
EEMD-LSSVM	1.0273	1.3856	0.1194	0.9045	0.8837	1.0980	0.1158	0.9518
EEMD-LSTM	1.0084	1.2887	0.1148	0.9174	0.8824	1.1058	0.1148	0.9511
Proposed	0.9775	1.2712	0.1127	0.9196	0.8720	1.0921	0.1132	0.9523

The bold values mean the best results among all the comparative models.

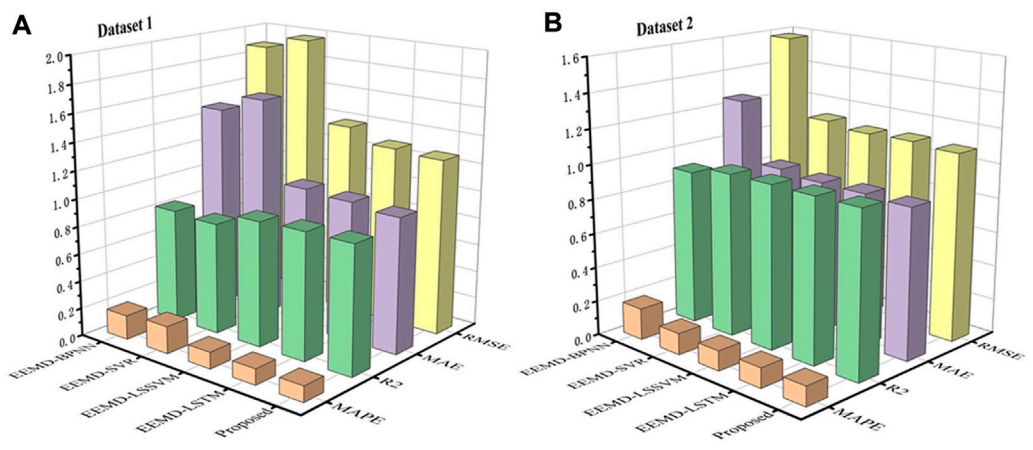


FIGURE 7
Result comparison of five models on experiment II (A) Dataset 1. (B) Dataset 2.

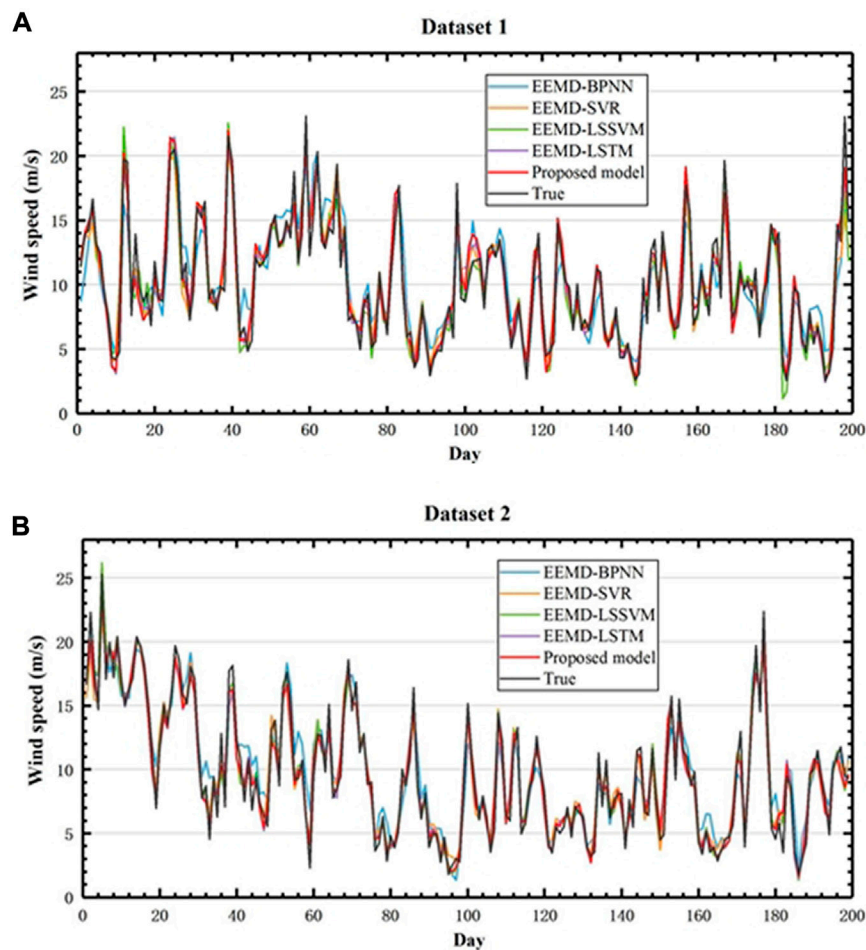


FIGURE 8
The line chart of forecasting results on experiment II (A) Dataset 1. (B) Dataset 2.

comparative models, but also largely improves the accuracy of forecasting results.

- (2) The forecasting accuracy of processing-based models is obviously higher than that of other single models, implying that data preprocessing algorithms included in the combined model can greatly contribute to better forecasting performance.
- (3) By integrating the high-frequency ability of LSTM and low-frequency ability of LSSVM model, the combined LSTM-LSSVM predictor can remarkably improve the forecasting accuracy, which further verifies the effectiveness of the developed combined mechanism in improving the prediction accuracy and ability.
- (4) For both two datasets, the values of four performance metrics obtained by single benchmark models are all worse than those of four metrics obtained by hybrid models, suggesting that the hybrid model has great advantages over the single one.

4 Conclusion

Accurate wind speed prediction plays a vital role in the security and stability of wind power grid-connected system. This paper proposed a novel combined prediction model based on EEMD, LSSVM, and LSTM neural network. To make data sequence more stable and certain, EEMD was first employed to decompose original signal data into a series of sub-layers. At the same time, in order to reduce workload and accumulated error, sample entropy was used to reconstruct the IMF components according to the SE values of sub-layers to obtain new subsequences with different frequencies. Since the subsequences of different frequencies contain different characteristic information, two prediction models, namely LSSVM and LSTM neural networks, were selected to respectively train and forecast high-frequency and low-frequency components. The ultimate predicted values were obtained by superimposing all the predicted values of two models. To investigate the impacts of signal processing method and combined mechanism on the forecasting

accuracy respectively, two group different models, namely single benchmark models and hybrid benchmark models, were compared using two wind speed datasets.

By analyzing experiment results, conclusions can be drawn as follows: 1) Whether dataset 1 or dataset 2 with volatility and uncertainty, experiments I-II indicated that the proposed hybrid EEMD-LSTM-LSSVM model can obtain a satisfactory forecasting performance in terms of four performance metrics. 2) Compared with single models, the superior ability of decomposition-based models has been evidenced, that is, the hybrid model based on signal processing method has significant influence on improving the forecasting performance. 3) The proposed model in this paper respectively trains and predicts high-frequency and low-frequency sequences mainly based on two different prediction models, and the combined mechanism of different predictors adopts different learning methods and training rules for different feature sequences to improve the prediction accuracy.

Despite the above mentioned interesting conclusion, the practical inspirations of this paper are worth mentioning. To the best of our knowledge, wind power generation has served for smart grid, smart microgrids, smart buildings and smart homes, and has a significant impact on electricity supply. However, the difficulty in wind power generation is attributed to unsatisfied wind speed forecasting results restricted by the nonlinearity and non-stationarity of wind speed data. In other words, wind speed prediction has become an important component of wind power generation and simultaneously affects the reliability and stability of wind farm and wind power grid connection system. As a result, the hybrid model proposed in this paper not only improves the accuracy and stability of wind speed prediction, but also has significant reference value for the scheduling, management and optimization of wind farms. For future research, there are two directions remaining to be explored. On the one hand, meteorological factors related to wind power generation, such as temperature, humidity and wind direction, have influence on wind speed, making it interesting to incorporate these meteorological factors instead of single wind speed time series. On the other hand, it is a promising subject to design advanced intelligence optimization algorithms to search for the key

parameters of deep learning network so as to further improve forecasting accuracy.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: <https://www.kaggle.com/datasets>.

Author contributions

XA: writing—review and editing, supervision, and funding acquisition. SL: methodology, software, and writing—original draft. HX: project administration, validation, and funding acquisition.

Funding

This work was jointly supported by National Natural Science Foundation of China (grant numbers 71901167 and 71701212) and the Project of Science and Technology Research Program of Hubei Provincial department of Education (grant number Q20191102).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 05 August 2022

ACCEPTED 27 September 2022

PUBLISHED 09 January 2023

CITATION

Xu J, Ji Z, Liu X, Bao Y, Zhang S, Wang W
and Pang Z (2023), Two-stage
scheduling of integrated energy
systems based on a two-step DCGAN-
based scenario prediction approach.
Front. Energy Res. 10:1012367.
doi: 10.3389/fenrg.2022.1012367

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Two-stage scheduling of integrated energy systems based on a two-step DCGAN-based scenario prediction approach

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Integrated energy systems (IESs) are developing rapidly as a supporting technology for achieving carbon reduction targets. Accurate IES predictions can facilitate better scheduling strategies. Recently, a newly developed unsupervised machine learning tool, known as Generative Adversarial Networks (GAN), has been used to predict renewable energy outputs and various types of loads for its advantage in that no prior assumptions about data distribution are required. However, the structure of the traditional GAN leads to the problem of uncontrollable generations, which can be improved in deep convolutional GAN (DCGAN). We propose a two-step prediction approach that takes DCGAN to achieve higher accuracy generation results and uses a K-means clustering algorithm to achieve scenario reduction. In terms of scheduling strategies, common two-stage scheduling is generally day-ahead and intraday stages, with rolling scheduling used for the intraday stage. To account for the impacts on the prediction accuracy of scheduling results, Conditional Value at Risk (CVaR) is added to the day-ahead stage. The intraday prediction process has also been improved to ensure that the inputs for each prediction domain are updated in real-time. The simulations on a typical IES show that the proposed two-step scenario prediction approach can better describe the load-side demands and renewable energy outputs with significantly reduced computational complexity and that the proposed two-stage scheduling strategy can improve the accuracy and economy of the IES scheduling results.

KEYWORDS

integrated energy system, scenario generation, optimal scheduling, energy scheduling, energy internet, integrated multienergy system

Abbreviations: IES, integrated energy system; GAN, Generative Adversarial Networks; DCGAN, deep convolutional Generative Adversarial Networks; CVaR, Conditional Value at Risk; SSE, sum of squares of the errors; MAPE, mean absolute percentage error.

1 Introduction

The IES is an important way of improving energy efficiency through the integrated planning and coordinated operation of multi-energy systems (Wu et al., 2016). Optimal scheduling of IES is a prerequisite for achieving a balance between supply and demand and efficient use of energy in IES with multi-energy coupling characteristics (Xue, 2015; Sun et al., 2018). While the uncertainty is high for multiple sources and loads in IES (Shabanpour-Haghighi and Ali Reza, 2016). Considering this, Accurate predictions can help decision makers to provide more economical scheduling strategies (Patel, 2005; Holtinen et al., 2007; Wu et al., 2012; Hu and Li, 2019), and they can also achieve more consumption of renewable energy (Yang et al., 2022).

Existing scenario generation methods are mainly model-driven and data-driven. The former contains many classic methods. A. Shamshad et al. (2005) used first and second-order Markov chains for wind speed scenario generation. Wu et al. (2007) used Monte Carlo methods to construct scenario trees for generation units and load prediction. The time series method is also a widely used technique for scenario generations. Morales et al. (2010) used the autoregressive moving average (ARMA) model to generate spatio-temporal scenarios with a given generation profile by assuming a linear correlation of the wind samples. Díaz et al. (2016) studied ARIMA models in state space (SS) and then extended the SS models to include correlated wind speeds at different locations. The method was enhanced by using an artificial neural network with a normal distribution approximation to capture non-linear dependencies and create representative scenarios (Vagropoulos et al., 2016). Although easy to implement, with simple statistical assumptions, model-driven methods are prone to over-fitting. And the above methods use historical data to build probability models that follow particular distributions and combine them with sampling methods to obtain the generated scenarios. This may limit the variety of scenarios generated and is not compatible with the actual complex application environment.

In recent years, data-driven methods have developed rapidly. They mainly utilize deep learning algorithms, and the development of artificial intelligence techniques allows data-driven scenario generation methods to describe the uncertainties of energy sources and loads more realistically (Chen Q et al., 2019; Cheng et al., 2021; Guo L. N et al., 2021). A radial basis function neural network algorithm was combined with a particle swarm optimisation approach to generate scenes using numerical weather forecasts as input (Sideratos and Hatziaargyriou, 2012). Liao et al. (2022) redesigned the structure and parameters of the original pixel convolutional neural network and obtained more accurate prediction results. Li et al. (2022) combined back propagation neural networks with an improved particle swarm algorithm to develop a prediction method for electricity consumption. Compared to model-driven methods, data-driven methods can

better characterize integrated energy systems. However, the performance of these methods relies on a careful selection of input features and is therefore not sufficiently flexible and reliable in practice (Cheng and Yu, 2019).

Another data-driven method is based on generative adversarial networks (GAN) (Goodfellow et al., 2014), which is known as a set of innovative generative models for reproducible scenario generation and has received a lot of attention in recent years. GAN was proposed in 2014 (Goodfellow et al., 2014). It was first used for image recognition but has recently also shown great results in the prediction of sources and loads for integrated energy systems (Lei et al., 2021; Hu et al., 2021). Chen Y et al. (2019) used GAN to generate scenarios of real wind and photovoltaic (PV) power distributions without complex statistical assumptions and sampling. Dong et al. (2022) used GAN to generate renewable energy scenarios with high accuracy. Chen Y et al. (2018) proposed a Bayesian GAN to successfully capture different patterns of historical data. Compared with other data-driven methods, these GAN-based ones can provide a more accurate generation process by reflecting the dynamic characteristics of energy resources with a full diversity of patterns (Dong et al., 2022).

Although a GAN-based scenario generation method can be applied to different situations easily, the problems of training difficulties, pattern collapse, and uncontrollable generated scenarios still arise in applications (Radford et al., 2016). Deep convolutional GAN (DCGAN) introduces convolutional generative networks, which has greatly improved network stability, convergence speed, and generated data quality (Radford et al., 2016; Wang and Liu, 2020).

On the other hand, the plenty of scenarios generated by the above methods become redundant initial inputs, significantly increasing the solution complexity and computational burden (Li et al., 2016; Hu et al., 2019). To reduce the number of scenarios generated, Lin et al. (2022) developed a multi-scenario stochastic programming model. Heitsch and Römis, 2003 proposed simultaneous backward approximation and fast forward selection based on probabilistic distances. However, the time complexity of such methods is at least proportional to the problem size, and the computational cost is enormous when the number of original scenarios is large. When processing sources and loads data of IES, Clustering and scenario reduction are very similar in basic ideas (Kwedlo and Łubowicz, 2021). The K-means clustering algorithm is an unsupervised learning algorithm and its computational complexity is not as sensitive to the size of the original scenario as traditional scenario reduction methods (Wang et al., 2018; Niu et al., 2021). Li et al. (2021) performed a clustering analysis of PV output based on this method, which effectively achieved scene reduction and improved prediction accuracy.

Meanwhile, the two-stage scheduling (day-ahead and intraday scheduling) approach is commonly used in cases such as electricity markets and optimal scheduling (Handschin and Slomski, 1990; Guo S et al., 2021; Cheng L. F et al., 2022). Zhou et al. (2016) investigated the scheduling method for aggregators to arbitrage in the intraday electricity market by using trading data from the day-ahead electricity market. Li and Zhang, 2021 used a multi-time scale model for day-ahead and intraday prediction of PV outputs. Cheng L. F et al. (2022) proposed a new dynamic robust optimisation scheduling strategy for coordinated microgrid operations, including both day-ahead scheduling scales and intraday scheduling scales. Yang et al. (2022) proposed a hierarchical rolling scheduling model.

All of the above studies have verified the feasibility and economy of two-stage scheduling through specific examples, but these scenarios are focused on power systems and rarely appear in IES. The uncertainties of sources and loads are even greater in IES, and even if the prediction accuracy can be improved, for example through the two-step prediction approach proposed in this paper, the design of the objective function requires further thought. Considering this, we introduce the Conditional Value-at-Risk (CVaR) (Asensio and Contreras, 2016; Cheng Z. P et al., 2022) into the objective function of the day-ahead stage to quantify the risk associated with uncertainties.

To reduce the errors between the generated scenarios and the actual scenarios and to ensure the economy and reliability of the IES scheduling plan, we proposed a two-stage optimisation strategy combined with the traditional ones. The strategy takes into account the risks at the day-ahead stage, dynamically adjusts the intraday state based on the day-ahead scenario information and uses a scheduling plan to improve the accuracy of the optimisation results and further match the actual scenario requirements.

The main contributions are as follows:

- A two-step prediction approach that takes DCGAN to achieve higher accuracy in generation results and that uses a K-means clustering algorithm to for scenario reduction is proposed. DCGAN can describe the uncertainties of sources and loads through unsupervised learning more realistically. It also solves the problems of training difficulties and pattern collapse that occur in GAN in data training. The K-means clustering algorithm effectively overcomes the shortcomings of some reduction methods that are sensitive to the size of the original scenario and better achieves a trade-off between computation time and solution accuracy. The scenario prediction approach proposed in this paper combines scenario generation and scenario reduction and achieves accurate prediction results.
- A two-stage IES scheduling strategy that considers multiple energy flows on day-ahead and intraday is developed. In the day-ahead scheduling stage, the CVaR was introduced for risk consideration. The intraday stage enables intraday rolling

optimisation based on the results of day-ahead scheduling. This approach effectively reduces errors in the prediction of IES sources and loads due to the single day-ahead scheduling, improving the accuracy of IES scheduling results while reducing system scheduling costs.

2 Two-step scenario prediction approach

Scenario prediction provides the data basis for scenario reduction, with the objective function is the optimisation of the generated data. The proposed scenario prediction approach first develops a step of DCGAN-based scenario generation, followed by a step of a K-means clustering algorithm-based scenario reduction step. Scenario reduction optimises the scenario generation with the highest scenario retention as the optimisation goal. The prediction method ensures that the reduced scenario set learns sufficiently about the implicit distribution of the historical real data set under the interaction of multiple non-linear factors, while significantly reducing the computational cost. The overall flow of the scenario prediction is shown in Figure 1.

2.1 Step 1: Scenario generation by deep convolutional GAN

The scenario generation stage feeds the historical dataset into DCGAN for the generation of scenarios. DCGAN is improved from GAN. GAN, which was proposed in 2014 and was initially used in the field of image recognition, is inspired by the zero-sum game in game theory. The two sides of the game are the generator (G) and the discriminator (D) (Lin et al., 2022). The generator simulates the generation of new data samples by learning the underlying distribution of real data. The discriminator is used to determine as accurately as possible whether the input data is real data or fake data generated by the generator. The game is played until G and D reach a “Nash equilibrium”. However, the discriminator is not able to determine whether the generator is generating the specified data as the generator’s generation content cannot be controlled, making it prone to problems such as pattern collapse and uncontrollable generation process during training (Dong et al., 2022). To address this problem, DCGAN introduces convolutional neural networks in the generators and discriminators of the GAN to replace the multi-layer perceptron in the GAN. This improves the effectiveness of the generator in generating data and the ability of the discriminator in discriminating data, and DCGAN can learn the mapping relationships between noise distributions that satisfy the conditions and the real data training set (Iliyasu and Deng, 2020).

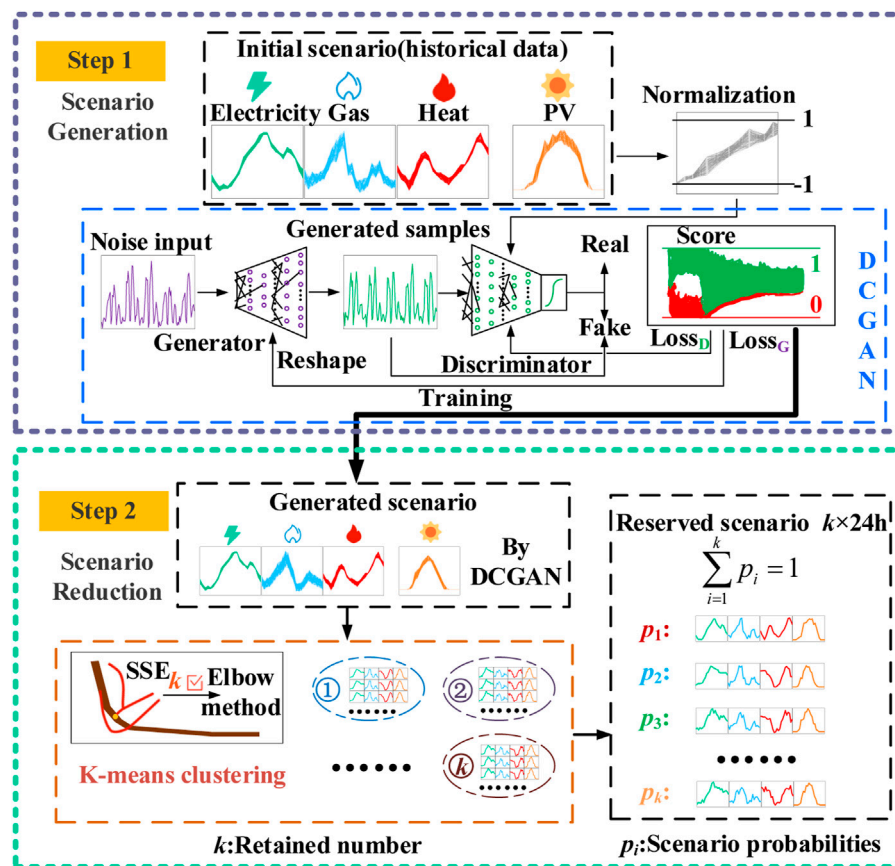


FIGURE 1
The overall flow of the two-step containing scenario generation and reduction.

In the proposed DCGAN, we use a two-part alternating optimisation procedure in its training process, which can be understood as a maximum-minimum optimisation problem. The first part maximises $V(D, G)$ from the discriminator side and the second part maximises $V(D, G)$ from the generator side. The objective function for DCGAN training is:

$$\min_G \max_D V(D, G) = E_{x \sim P_X} [\log D(x)] + E_{z \sim P_Z} [\log(1 - D(G(z)))] \quad (1)$$

where E represents the expected value; $D(G(z))$ is the probability that the generated data $G(z)$ will be judged true in D ; $D(x)$ represents the probability that the real data x will be judged true in D ; the distribution of the noisy data z is $z \sim P_Z$; P_X is the real distribution of the electrical, gas and thermal load and PV output data x .

The scenario generation network is trained by gaming the generators and discriminators of DCGAN. The network learns the implicit patterns in historical datasets and generates generative datasets judged to be “true,” which can be used to simulate electricity, gas and heat loads and PV outputs. This provides a rich and reliable collection of data for subsequent IES scheduling plans.

2.2 Step 2: Scenario reduction by K-means clustering

The computation of DCGAN-generated scenarios increases exponentially with the size of the scenario, so scenario reduction is performed at this stage to reduce the computation of subsequent scheduling. The K-means clustering method continuously computes the shortest distance from each sample point to the centre of mass by iteration, updating the position of the centre of mass so that the loss function corresponding to the clustering result is minimised. The loss function is defined as the sum of squares of the errors from the sample points to the centre of mass SSE, representing the superiority or inferiority of the clustering effect.

$$SSE = \sum_{q=1}^k \sum_{p \in C_q} |p - m_q|^2 \quad (2)$$

where C_q is the q th cluster, p is the sample point in C_q , m_q is the centre of mass of C_q (the mean of all samples in C_q), k is the number of cluster centres.

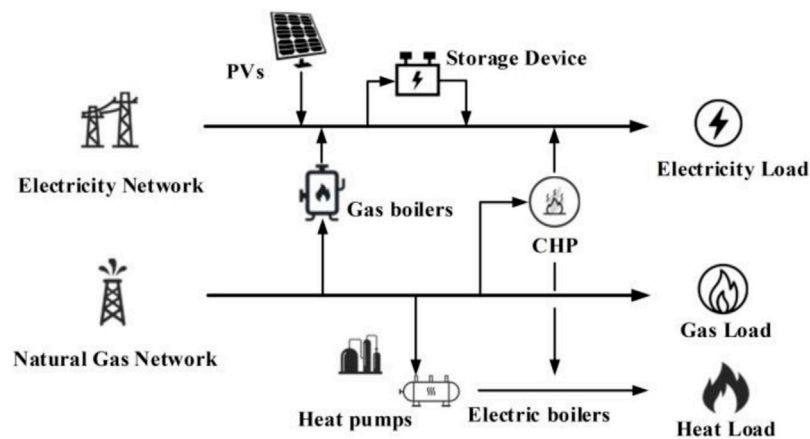


FIGURE 2
The structure of IES.

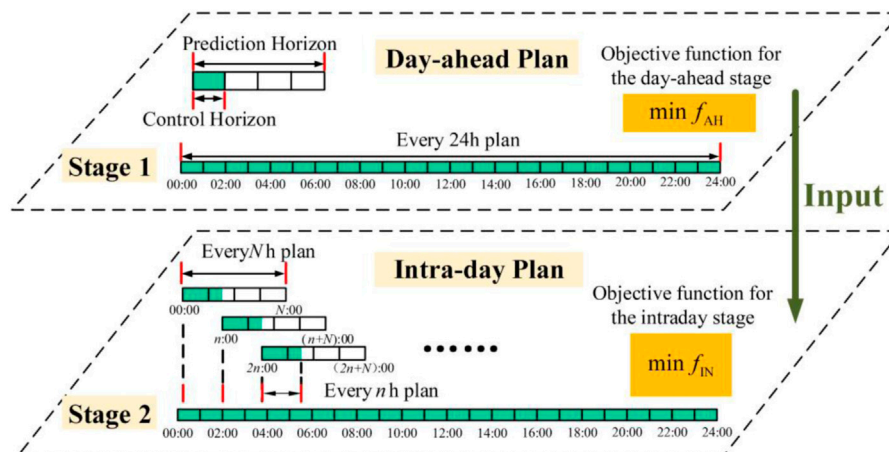


FIGURE 3
Two-stage optimisation process.

The Elbow Method, which is easy to implement and effective, is adopted to confirm the number of K-means clustering centres (Chen Q et al., 2019). All scenarios are classified into k categories. The attributes and characteristics of the reduced data scenarios are significantly different. The probability of each scenario after reduction is the number of scenarios in the category divided by the total number of scenarios.

3 Two-stage scheduling objective

Typical components in an IES are shown in Figure 2. As can be seen, there are multiple sources and multiple loads in the IES, which is more complex than the power systems. The source side includes electricity and natural gas, and the load side includes

electrical, gas and thermal loads. New energy generation and energy storage are also considered.

Figure 3 demonstrates the common two-stage scheduling structure. Day-ahead and intraday stages are considered for scheduling IES resources and economic scheduling models are developed. The day-ahead plan is based on a 24-h scheduling cycle with a 1-h time scale. Considering that the uncertainties of scenario prediction can have an impact on the economy of IES scheduling, the day-ahead plan combines CVaR to optimise the economics of the next day's integrated energy system to determine the day-ahead prediction results. However, due to prediction errors, it is often difficult to meet the actual energy demand of customers before the day plan. In the intraday stage, the intraday rolling optimisation method based on DCGAN predictions is used to correct the day-ahead plan for

equipment outputs. The prediction horizon is Nh , and the control horizon is nh (i.e., in a single prediction, the equipment output schedule for the next N hours is optimised by predicting the loads and outputs for the next N hours, but only the outgoing arrangements for n momentary points will be implemented). The day-ahead stage is used as the initial input to the intraday stage, and the intraday stage corrects the day-ahead stage. The two-stage optimisation process for the day-ahead and intraday stages is shown in Figure 3.

3.1 Scheduling objective in the day-ahead stage

To achieve better scheduling of the integrated energy system, a day-ahead optimisation model is constructed with the sum of energy purchase cost, operation cost and renewable energy consumption cost as the economic optimisation objective.

$$\min f = \sum_{t=1}^T \left(c_e P_e^t + c_g V_g^t + c_h P_h^t + c_a P_a^t + \sum_{i \in I} c_i P_i^t \right) \quad (3)$$

where, c_e , c_g and c_h are the cost factors for electricity, gas and heat respectively; P_e^t and P_h^t are the amount of energy purchased by the system from the superior electricity and heat networks respectively at time t ; V_g^t is the amount of gas purchased by the system from the superior gas network at time t ; c_a is the penalty factor for light abandonment; P_a^t is the amount of light abandoned by the system at time t ; I is the set of energy conversion equipment; c_i is the operating cost factor for equipment i ; P_i^t is the output of the equipment at time t .

CVaR is often introduced into system models for risk management when dealing with optimisation problems that take uncertainties into account, such as in power systems. The CVaR quantifies the worst-case tail loss, i.e., the expected loss over the value at risk (Fu et al., 2020). Due to the large errors in day-ahead scheduling, CVaR is introduced in this paper to quantify the risk posed to IES scheduling in the presence of the uncertainties of sources and loads. The objective function is as follows.

$$\min f_{AH} = \lambda E(f) + (1 - \lambda) \text{CVaR}_\alpha(f) \quad (4)$$

where, $E(f)$ is the desired operating cost; CVaR_α is CVaR for a confidence level of α ; λ is the trade-off between the desired operating cost and the risk of operating cost fluctuations; f is the objective function of the multi-scenario conventional scheduling model.

Eq. 4 can be transformed into:

$$\begin{aligned} \min f_{AH} = & \lambda \cdot \sum_{b \in \Omega_b} \pi_b \left[\sum_{t=1}^{24} \left(c_e P_e^t + c_g V_g^t + c_h P_h^t + c_a P_a^t + \sum_{i \in I} c_i P_i^t \right) \right] \\ & + (1 - \lambda) \cdot \left(\zeta + \frac{1}{\alpha} \sum_{b \in \Omega_b} \pi_b z_b \right) \end{aligned} \quad (5)$$

$$\text{s.t.} \quad z_b \leq \sum_{t=1}^{24} \left(c_e P_e^t + c_g V_g^t + c_h P_h^t + c_a P_a^t + \sum_{i \in I} c_i P_i^t \right) - \zeta, z_b \leq 0 \quad (6)$$

where, Ω_b is the set of previously reserved scenarios; b means the b th scenario in the set of previously reserved scenarios; π_b is the probability of the b th scenario occurring; ζ and z_b are intermediate parameters with no clear physical meaning.

According to the components considered in Figure 2, the constraints for the day-ahead stage include:

$$P_{GT,e}^t + P_e^t - P_{HP,e}^t - P_{EB,e}^t - L_e^t = 0 \quad (7)$$

$$P_g^t - P_{GT,g}^t - P_{GB,g}^t - L_g^t = 0 \quad (8)$$

$$\sigma_h \eta_{HE} (P_h^t + P_{HRSG,h}^t + P_{HP,h}^t + P_{EB,h}^t + P_{GB,h}^t) - L_h^t = 0 \quad (9)$$

$$0 \leq P_{BAT,in}^t \leq P_{BAT}^{\max}, \text{ in } 0 \leq P_{BAT,out}^t \leq P_{BAT,out}^{\max} \quad (10)$$

$$W_{BAT}^{\min} \leq W_{BAT}^t \leq W_{BAT}^{\max} \quad (11)$$

$$P_i^{\min} \leq P_i^t \leq P_i^{\max}, \forall i \in I \quad (12)$$

$$P_{i,r}^{\text{down}} \leq P_{i,r}^{t+1} - P_{i,r}^t \leq P_{i,r}^{\text{up}}, \forall i \in I \quad (13)$$

where, $P_{GT,e}^t$ is the power generated by the gas turbine at time t ; $P_{HP,e}^t$ is the input electric power of the heat pump at time t ; $P_{EB,e}^t$ is the input electric power of the electric boiler at time t ; L_e^t is the electric load of the consumer at time t ; $P_{GT,g}^t$ is the gas consumption of the gas turbine at time t ; $P_{GB,g}^t$ is the gas consumption of the gas boiler at time t ; L_g^t is the gas load of the consumer at time t ; σ_h is the heat distribution coefficient; η_{HE} is the efficiency of the heat exchange equipment; $P_{HRSG,h}^t$ is the heat power generated by the waste heat boiler at time t ; $P_{HP,h}^t$ is the output heat power of the heat pump at time t ; $P_{EB,h}^t$ is the output heat power of the electric boiler at time t ; $P_{GB,h}^t$ is the output thermal power of the gas boiler at time t ; L_h^t is the thermal load of the user at time t ; $P_{BAT,in}^t$ and $P_{BAT,out}^t$ are the charging and discharging power of the storage device respectively; $P_{BAT,in}^{\max}$ and $P_{BAT,out}^{\max}$ are the maximum charging and discharging power respectively; W_{BAT}^t is the stored electrical energy at time t ; $W_{BAT}^{\min}$ and $W_{BAT}^{\max}$ are the minimum and maximum stored electrical energy respectively; $P_i^{\min}$ and $P_i^{\max}$ are the minimum and maximum output of device i respectively; $P_{i,r}^{\text{down}}$ and $P_{i,r}^{\text{up}}$ are the downward and upward climbing power of device i respectively.

3.2 Scheduling objective in the intraday stage

The expression for the integrated energy system intraday optimisation objective function is as follows.

$$\min f_{IN} = \sum_{t=t_0}^{t_0+1} \left(c_e P_e^t + c_g V_g^t + c_h P_h^t + c_a P_a^t + \sum_{i \in I} c_i P_i^t \right) \quad (14)$$

The intraday stage also uses the DCGAN method for scenario generation. The difference is that the intraday scenarios are based on the previous moment's data as input, and a large collection of

historical data is used as a learning sample to generate the next set of scenarios every other moment, moving backward in time window in turn until a set of intraday scenarios is generated. The intraday scenario expressions are as follows.

$$\begin{cases} x_{s,t_0+k\Delta t} = f(x_{p,t_0+k\Delta t}, u_{s,t_0+k\Delta t}) \\ \sum \pi_{s,t_0+k\Delta t} = 1 \quad \forall k = 1, 2, \dots, n-1 \end{cases} \quad (15)$$

where, s is the total number of scenarios at $t_0 + k\Delta t$ time, $x_{s,t_0+k\Delta t}$ is the scenario of sources and loads at $t_0 + k\Delta t$ time, $x_{p,t_0+k\Delta t}$ is the scenario of sources and loads at the previous time, $u_{s,t_0+k\Delta t}$ is the historical scenario of sources and loads at $t_0 + k\Delta t$ time; $\pi_{s,t_0+k\Delta t}$ is the probability of the scenario at $t_0 + k\Delta t$ time.

The components in the IES remain unchanged, so the constraint in Eq. 13 remains the same, i.e., Eqs 7–13.

4 Case study

4.1 Simulation setup

The data of electricity, gas and thermal loads and PV output are chosen (Tian et al., 2019; Chen Y et al., 2018; Chen B. Y et al., 2018). The number of scenarios per arithmetic case is 2,880, and the data is 11,520. The hardware platform used for DCGAN training is an AMD-Ryzen5-5600H CPU and an NVIDIA-GeForce-RTX3050Ti GPU. The DCGAN model uses Tensorflow 2.4.0 as the framework for deep learning. To reduce the time required for scenario generation, the GPU is called upon for efficient parallel computing to increase the efficiency of model training. The scenario generation part is trained by Pycharm calling the virtual environment created in Anaconda, and the scenario reduction part is implemented by Matlab. The prediction domain in intraday rolling optimisation is taken as 4 h and the control domain as 1 h. The confidence level α is 0.9 and the risk appetite weighting factor λ is 0.4. The scheduling model was solved via a CPLEX solver.

In terms of DCGAN structure parameters, both D and G include three convolutional layers, with a step size of 1 and 7 convolutional kernels. To accelerate convergence and mitigate overfitting, a batch normalisation layer with a momentum of 0.8 is added between the convolution layers. The number of G convolutional layer filters is 80, 60, and 40 in that order, and the number of D convolutional layer filters is 120, 140, and 160 in that order. The activation function for the three convolutional layers of G is ReLU, the activation function for the three convolutional layers of D is LeakReLU, and Tanh is used as the activation function in the final layer. The specific parameter settings of DCGAN are shown in Table 1.

The main economic parameters and equipment parameters involved in the system are shown in Tables 2, 3 respectively.

4.2 Analysis of scenario prediction results

4.2.1 Analysis of prediction results for the day-ahead stage

As shown in Figures 4, 5, the scenarios generated by GAN and DCGAN respectively are retained by K-means clustering. The top part of each subfigure shows the generations, and the bottom part shows the reductions. The number of retained scenarios was determined by the elbow method. The core metric of the elbow method is the sum of the squared errors (SSE), determined by Eq. 2. The elbow method was used on the data generated by GAN and DCGAN, respectively, and the resulting number of cluster centres was both 3. The original 120 days of initial historical data is reduced to three scenarios with probability, and each scenario has significantly different attributes and features after the reduction. The probability values for each of the reduced retained scenarios are shown in Table 4.

The mean absolute percentage error (MAPE) is chosen as the basis for comparison of the generated and retained scenarios with the actual data. The comparisons of the GAN-generated and DCGAN-generated scenarios with the real scenarios are shown in Figures 6, 7 respectively. As shown in Table 5, Compared to GAN, DCGAN is a more stable method for generating scenarios of sources and loads and can capture a range of iconic features of real scenarios, such as peaks and valleys, distributions, etc., more accurately. $MAPE_A$ is calculated from Eq. 15.

$$MAPE_A = \sum_{i=1}^k (p_i \cdot MAPE_i) \quad (16)$$

Where, p_i is the probability of occurrence of the corresponding scenario; $MAPE_i$ is the MAPE of the corresponding scenario.

4.2.2 Analysis of prediction results for the intraday stage

Intraday predictions are based on day-ahead predictions. In the two-stage prediction, the first stage involves predicting the input day-ahead scenario to assess uncertainties, and the second stage uses DCGAN to continuously predict shorter intervals of time-based on the day-ahead scenario, with the input of a continuously updated set of day-ahead scenarios for the rolling predictions. The comparisons of the day-ahead and intraday stages' retained scenarios with the actual scenarios are shown in Figure 8.

In contrast to the day-ahead prediction, which has a 24 h prediction domain, the intraday prediction has a 4 h prediction domain and a 1 h control domain. The intraday prediction uses the prediction domain data as the training set and the control domain results are the intraday prediction results for that hour, rolling the prediction until the 24 h prediction is completed. The difference in time interval Δt leads to a difference in the data input to DCGAN between the day-ahead and intraday stages, which affects the scenario

TABLE 1 Structural parameters of D and G.

Network layer		Structure and parameter size			Explanation of terms	
		Layer number	Generator	Discriminator		
Layer1, 2, 3	Convolution layer (filter, kernel_size, step size)	1	8, (3,3), 1	8, (3,3), 1	Convolution layer	For extracting image features
		2	16, (3,3), 1	16, (3,3), 1	Kernel_size	Determining the field of view for convolution
		3	8, (3,3), 1	32, (3,3), 1	Activation function	For non-linear integration
	Batch normalisation	Momentum = 0.8			Step size	Defining the step length of the kernel when traversing
	Activation function	LeakyReLU Alpha = 0.2			Batch normalisation	Making the distribution of individual features of the input data similar
	Dropout	Rate = 0.1			Momentum	For accelerated and consistent learning
Layer4	Dense	Units = 1			LeakyReLU, Tanh	Activation functions
	Activation function	4	Tanh	—	Units	Output dimension of this layer

TABLE 2 System economic parameters.

Economic parameters	Price
The low calorific value of natural gas	35.5 MJ/Nm ³
Natural gas prices	3.45 yuan/m ³
Electricity price	0.32 yuan/kWh from 00:00 to 7:00
	1.07 yuan/kWh from 09:00 to 11:00 and from 17:00 to 22:00
	0.65 yuan/kWh for other time
Household PV O and M costs	0.025 yuan/kWh
Cost of abandoned light	7 yuan/kWh

TABLE 3 System equipment parameters.

Equipment	Rated output (kW)	Minimum load factor	Power generation efficiency	Heat generation efficiency or COP	Operation and maintenance costs
CHP unit	250	0.2	24.3%	0.8	0.06
Gas boiler	100	0.1	—	0.96	0.02
Ground source heat pump	200	0.1	—	4.5	0.026
Electric boiler	72	0.2	—	0.98	0.013
Heat exchanger	—	—	—	0.9	0.2

prediction results. Prediction errors for intraday and day-ahead stage scenario generation using DCGAN are shown in Table 6. It can be seen that all three scenarios correspond to a

different degree of decrease in MAPE. The MAPE_A is 3.87%, which is further reduced compared to the MAPE_A in the day-ahead stage of 5.08%.

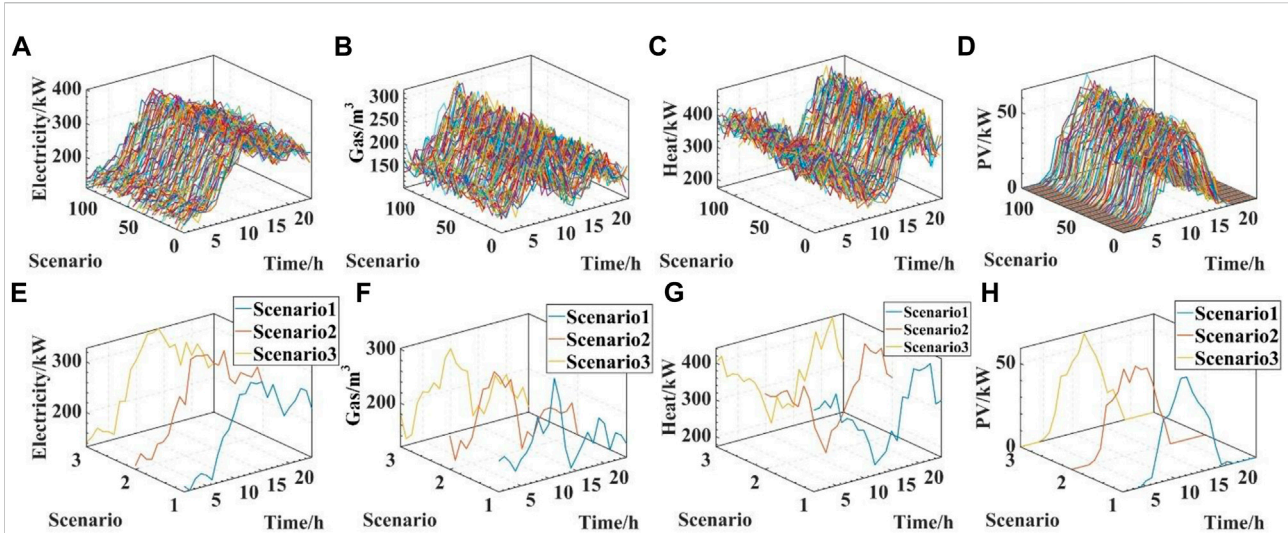


FIGURE 4

GAN-generated scenarios for: (A) electricity loads; (B) gas loads; (C) heat loads; (D) PV outputs; reduced scenarios by K-means clustering in the corresponding GAN-generated scenarios for: (E) electricity loads; (F) gas loads; (G) heat loads; (H) PV outputs.

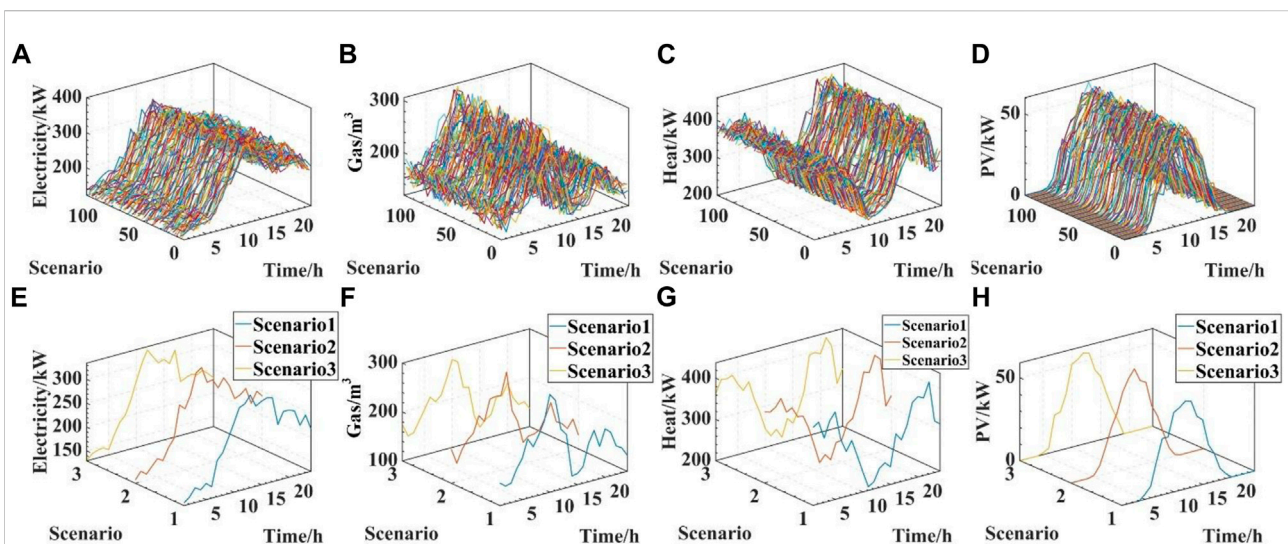


FIGURE 5

DCGAN-generated scenarios for: (A) electricity loads; (B) gas loads; (C) heat loads; (D) PV outputs; reduced scenarios by K-means clustering in the corresponding DCGAN-generated scenarios for: (E) electricity loads; (F) gas loads; (G) heat loads; (H) PV outputs.

TABLE 4 Probability of occurrence of retained scenarios.

Method	Scenario1 (%)	Scenario2 (%)	Scenario3 (%)
GAN	35.00	36.67	28.33
DCGAN	25.83	46.47	27.50

4.3 Analysis of the results of the scheduling operation

4.3.1 Analysis of the results of the day-ahead scheduling stage

In the day-ahead stage, DCGAN and GAN are used for scenario generation respectively, and the retained sources and

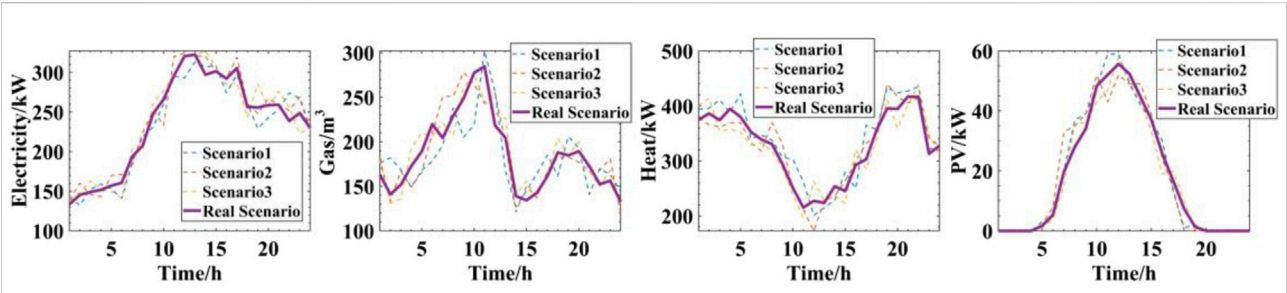


FIGURE 6 Comparisons of the scenarios generated by GAN in the day-ahead stage with the actual scenarios.

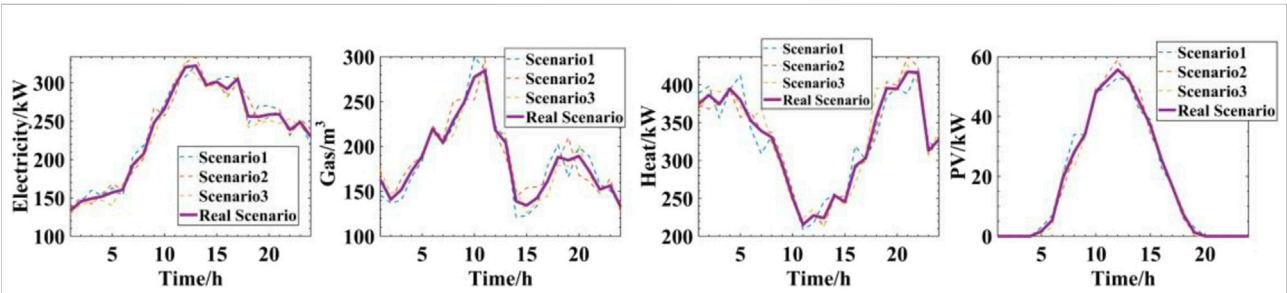


FIGURE 7 Comparisons of the scenarios generated by DCGAN in the day-ahead stage with the actual scenarios.

TABLE 5 Prediction errors for scenario generations in the day-ahead stage using DCGAN, GAN.

Method	Scenario	MAPE (%)	MAPE _A (%)
DCGAN	1	6.10	5.08
	2	4.43	
	3	5.25	
GAN	1	10.11	9.39
	2	9.65	
	3	8.16	

TABLE 6 Prediction errors for intraday and day-ahead stages' scenario generation using DCGAN.

Method	Scenario	MAPE (%)	MAPE _A (%)
Intraday prediction	1	5.04	3.87
	2	3.33	
	3	3.70	
Day-ahead prediction	1	6.10	5.08
	2	4.43	
	3	5.25	

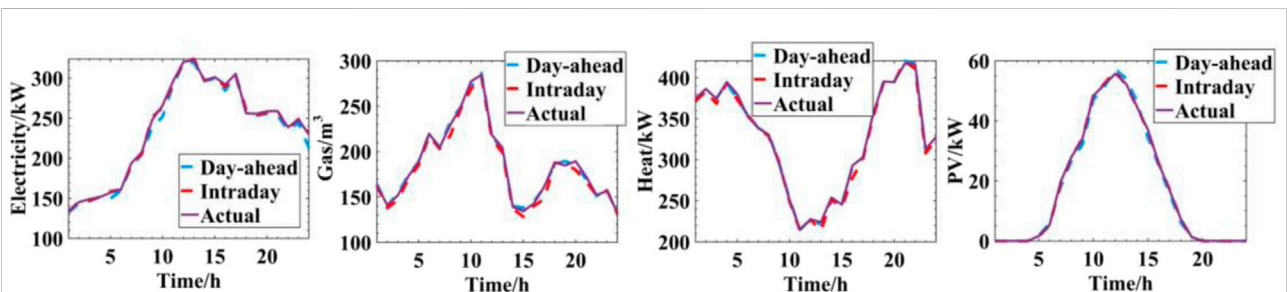


FIGURE 8 Comparisons of the day-ahead and intraday stages' retained scenario with the actual scenario.

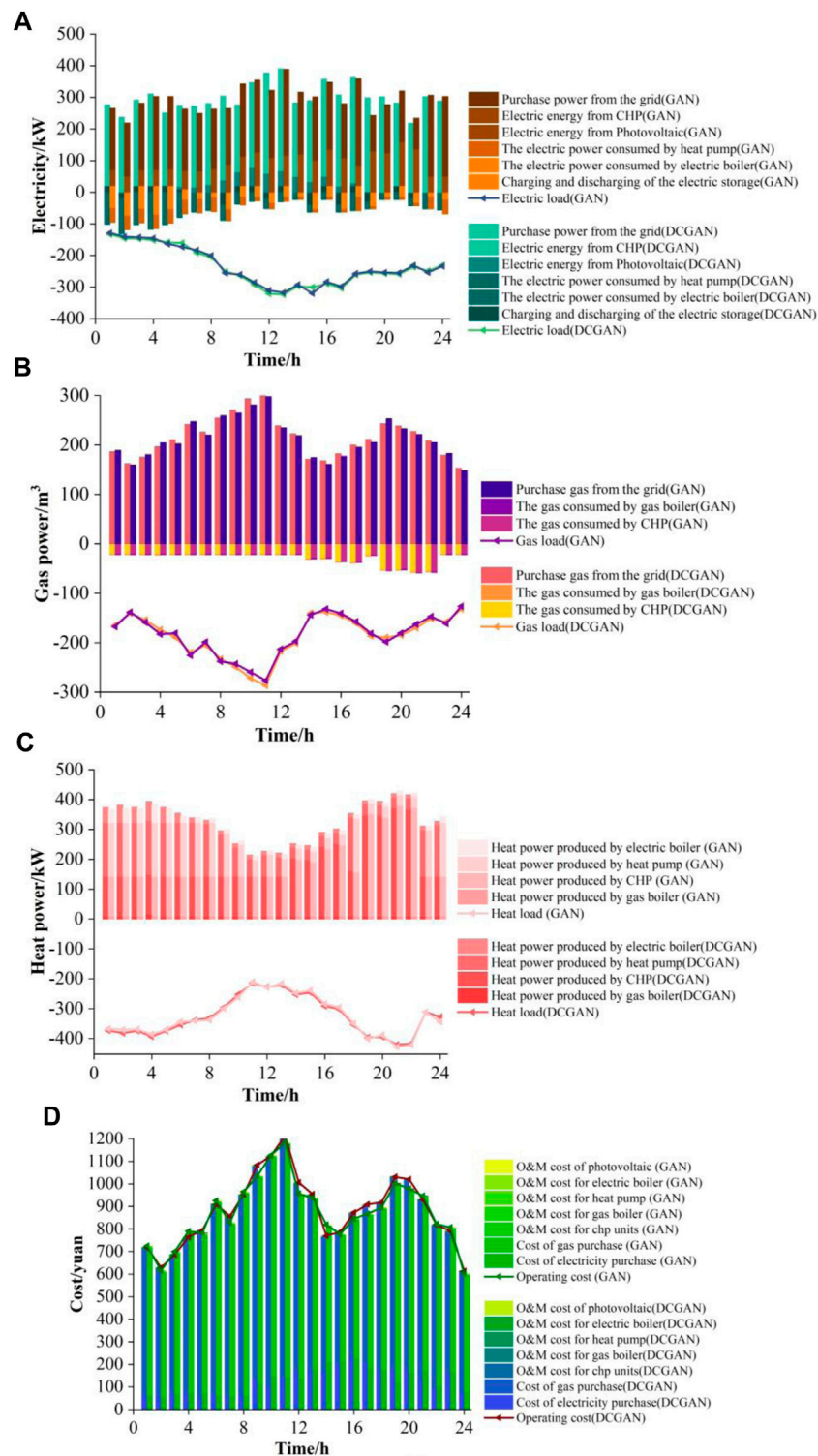
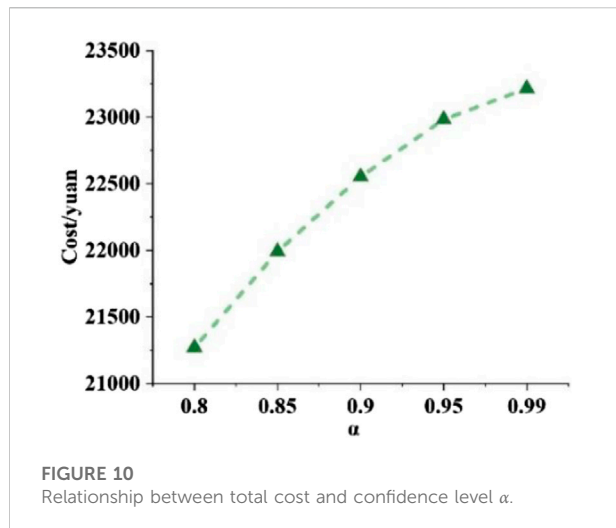


FIGURE 9
Comparisons of day-ahead scheduling results based on DCGAN scenario generation and GAN scenario generation:(A) electricity; (B) natural gas; (C) heat power; (D) cost.



loads data are weighted by the corresponding probabilities to obtain the scenarios involved in the actual scheduling, and the comparisons of the scheduling results are shown in Figure 9. As can be seen in Figure 9, PV equipment operates between 8:00 and 15:00, taking full advantages of the low O&M costs of PV equipment and increasing PV consumption. Electric boilers are put into use in large numbers at valley time tariffs to meet the larger heat loads in winter. 14:00–23:00 is the peak period for electricity consumption. Considering the peak electric charges and heat load demand, CHP works a lot during this period to meet the larger demand for electric and heat loads at a lower cost. During the day-ahead optimisation stage, the joint scheduling of the power systems, natural gas systems and thermal systems effectively relieves the pressure on the supply-demand balance and increase PV consumption. The differences in predicted data lead to different IES scheduling results. When scheduling based on DCGAN and GAN for scenario prediction respectively, the distribution and peaks of each energy flow are the same, but there are more differences in the scheduling results (especially for electrical energy). The difference between the actual value and the scenario generated by DCGAN is 5.08%, which is less than the error of 8.26% between the scenario generated by GAN and the actual value. Therefore, the scheduling results based on DCGAN for scenario generation are executed in the day-ahead scheduling stage.

For CVaR, Figure 10 explores the impact of a change in confidence level α on the total cost results of day-ahead scheduling.

Figure 10 shows the impact of different confidence levels on the total cost of ownership. Five scenarios are compared with settings $\alpha = 0.8, 0.85, 0.9, 0.95$ and 0.99 (with a risk factor of $\lambda = 0.4$). As the confidence level increases, the total cost of scheduling also increases, reflecting the increased level of risk aversion on the part of the decision-maker. Smaller values indicate that the decision-maker has a lower requirement for the safety and

reliability of the system and prefers a scheduling approach that improves the economic efficiency of the system operation. The risk factor λ is set to 1, i.e., the CVaR is not considered during the day-ahead scheduling stage. The comparison of the corresponding scheduling costs at this point with the scheduling costs for the scenarios set out (0.9 for α and 0.4 for λ) is shown in Table 7.

4.3.2 Analysis of the results of the intraday scheduling stage

In the intraday scheduling stage, 01:00–05:00 of the day is taken as the first Prediction Domain, and the first period, i.e., 01:00–02:00, is selected as the Control Domain, and the data input from 01:00–05:00 is used to develop the scheduling plan in the Prediction Domain, obtain the scheduling plan for that period, and execute the scheduling decisions in the Control Domain only. Scroll to the next period 02:00–06:00, select 02:00–03:00 as the optimisation result for that period, and so on until the operation optimisation is completed, and obtain the scheduling decision for the whole period of that day. The scheduling results for electricity, gas and heat for the intraday stage of the IES are shown in Figure 11.

The multi-energy flow scheduling in both day-ahead planning and intraday scheduling is on an hourly time scale, but the intraday prediction is more accurate than the day-ahead prediction, so the day-ahead scheduling instructions have been amended. The different scheduling strategies of the decision-makers result in different scheduling costs. The total cost of the two-stage rolling scheduling is 20,756.24yuan, which is 8.66% less than the cost of the day-ahead scheduling, making the two-stage scheduling more economical. Day-ahead scheduling input data is predicted on a 24-h basis, and due to its greater prediction error, the sources and loads uncertainties of the integrated energy system are greater and the predicted day-ahead scenario set error is greater. Decision-makers tend to make conservative scheduling decisions when considering large uncertainties, thus requiring consideration of conditional value-at-risk and resulting in higher scheduling costs. The time interval between the two stages of the scheduling update is 1 h, which produces a much smaller error. The two-stage rolling optimisation can be used to smooth out the uncertainties of sources and loads and give a more realistic decision solution so that the intraday rolling optimisation results in an improved scheduling economy.

5 Conclusion

In this paper, a DCGAN-based scenario prediction approach is used for multiple sources and loads of IES. At the same time, a two-stage scheduling model based on different objective functions to obtain better scheduling results from both day-ahead and intraday stages is also developed, which improves the economy while ensuring accuracy. The conclusions are as follows.

TABLE 7 Comparison of day-ahead scheduling costs considering CVaR and not considering CVaR.

Scenario	Not considering CVaR ($\lambda = 0$)	Considering CVaR ($\lambda = 0.4, \alpha = 0.9$)
Cost/yuan	21,153.34	22,553.41

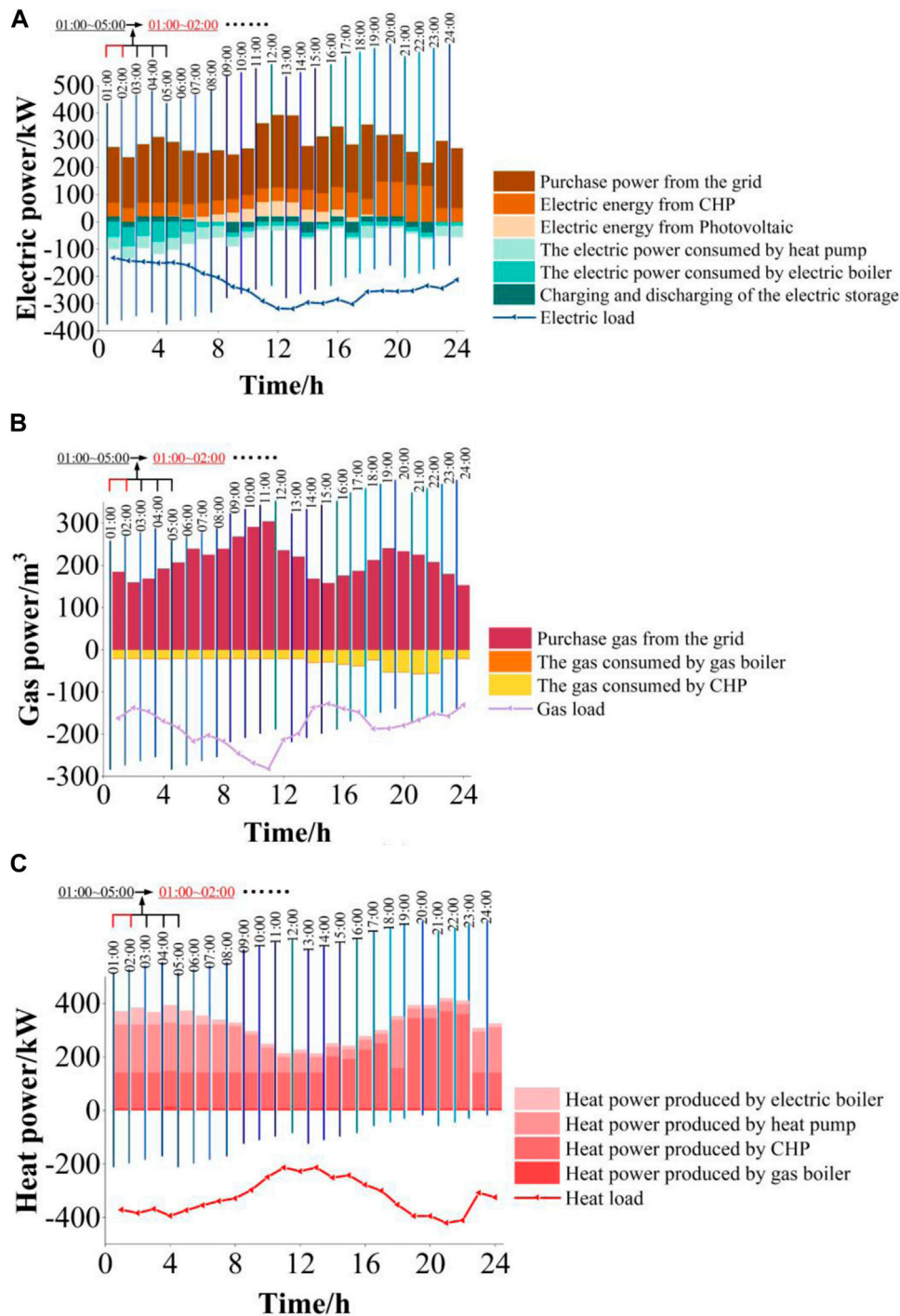


FIGURE 11
(Continued).

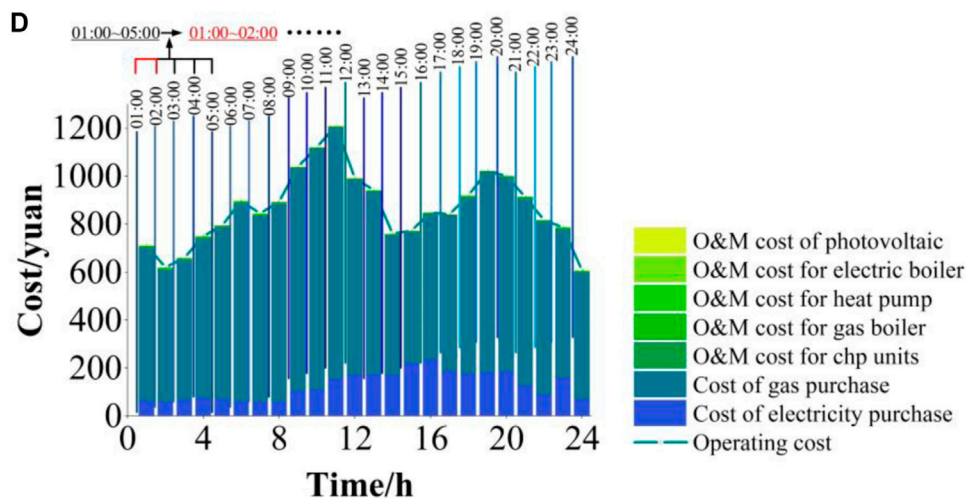


FIGURE 11
(Continued). Scheduling results for the intraday stage of the IES: (A) electricity; (B) natural gas; (C) heat power; (D) cost.

- (1) A two-step prediction approach is proposed in the scenario prediction process. We generate data of sources and loads based on DCGAN and use a K-means clustering algorithm for scenario reduction. The proposed scenario prediction approach efficiently and accurately characterises the load-side demands and renewable energy outputs of the IES, significantly reducing the computational complexity and providing reliable support for energy scheduling.
- (2) A two-stage scheduling strategy is developed by considering scenario prediction and scheduling update time scales. While further reducing prediction errors, the scheduling results considering CVaR are obtained for the intraday stage and the ones for the day-ahead stage improve the economy of IES.

This paper focuses on the problem of optimising IES scheduling at different time scales in the presence of uncertainties of sources and loads. Future work will explore the relationship between the relevant parameters of CVaR and DCGAN parameters to further achieve the trade-off between risk and prediction accuracy. The prediction and scheduling results of the sources and loads of IES in different prediction and control domains will also be considered.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

JX: Conceptualization, methodology, software, data curation, visualization, writing—original draft. ZJ: Funding acquisition, conceptualization, methodology, visualization, validation, writing—review and editing. XL: Conceptualization, funding acquisition. YB: Methodology, software. SZ: Data curation, software. WW: Methodology, software. ZP: Data curation, methodology.

Funding

This work was financially supported by the National Natural Science Foundation of China under Grant 52107100, the Natural Science Foundation of Jiangsu Province of China under Grant BK20190710, the Natural Science Research of Jiangsu Higher Education Institutions of China under Grant 20KJB470024, and the Key Research and Development Program of Jiangsu Province under Grant BE2020081-4.

Conflict of interest

JX, ZJ, XL, YB, SZ, WW, and ZP were employed by Jiangsu Provincial Integrated Gas-Electricity Interconnection Energy Laboratory and International Joint Laboratory of Integrated Energy Equipment and Integration in Jiangsu Province.

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Nomenclature

Variables

G generator

D discriminator

$V(D, G)$ objective function for DCGAN training

E expected value

$D(G(z))$ probability that the generated data $G(z)$ will be judged true in D

$D(x)$ probability that the real data x will be judged true in D

$z \sim P_Z$ distribution of the noisy data z

P_X real distribution of the electrical, gas and thermal load and PV output data x

C_q the q th cluster

p the sample point in C_q

m_q the centre of mass of C_q

k is the number of cluster centres

c_e, c_g, c_h cost factors for electricity, gas and heat respectively

P_e^t, P_h^t amount of energy purchased by the system from the superior electricity and heat networks respectively at time t

V_g^t amount of gas purchased by the system from the superior gas network at time t

c_a penalty factor for light abandonment

P_a^t amount of light abandoned by the system at time t I set of energy conversion equipment

c_i operating cost factor for equipment i

P_i^t output of the equipment at time t

$E(f)$ desired operating cost

$CVaR_\alpha$ CVaR for a confidence level of α

λ trade-off between the desired operating cost and the risk of operating cost fluctuations

f objective function of the multi-scenario conventional scheduling model

Ω_b set of previous reserved scenarios b the b th scenario in the set of previously reserved scenarios

π_b probability of the b th scenario occurring

ζ, z_b intermediate parameters with no clear physical meaning

$P_{GT,e}^t$ power generated by the gas turbine at time t

$P_{HP,e}^t$ input electric power of the heat pump at time t

$P_{EB,e}^t$ input electric power of the electric boiler at time t

L_e^t electric load of the consumer at time t

$P_{GT,g}^t$ gas consumption of the gas turbine at time t

$P_{GB,g}^t$ gas consumption of the gas boiler at time t

L_g^t gas load of the consumer at time t

σ_h heat distribution coefficient

η_{HE} efficiency of the heat exchange equipment

$P_{HRSG,h}^t$ heat power generated by the waste heat boiler at time t

$P_{HP,h}^t$ output heat power of the heat pump at time t

$P_{EB,h}^t$ output heat power of the electric boiler at time t

$P_{GB,h}^t$ output thermal power of the gas boiler at time t

L_h^t thermal load of the user at time t

$P_{BAT,in}^t, P_{BAT,out}^t$ charging and discharging power of the storage device respectively

$P_{BAT,in}^{\max}, P_{BAT,out}^{\max}$ maximum charging and discharging power respectively

W_{BAT}^t stored electrical energy at time t

$W_{BAT}^{\min}, W_{BAT}^{\max}$ the minimum and maximum stored electrical energy respectively

$P_i^{\min}, P_i^{\max}$ the minimum and maximum output of device i respectively

$P_{i,r}^{\text{down}}, P_{i,r}^{\text{up}}$ the downward and upward climbing power of device i respectively

s total number of scenarios at $t_0 + k\Delta t$ time

$x_{s,t_0+k\Delta t}$ scenario of sources and loads at $t_0 + k\Delta t$ time

$x_{p,t_0+k\Delta t}$ scenario of sources and loads at the previous time

$u_{s,t_0+k\Delta t}$ historical scenario of sources and loads at $t_0 + k\Delta t$ time

$\pi_{s,t_0+k\Delta t}$ probability of the scenario at $t_0 + k\Delta t$ time

p_i probability of occurrence of the corresponding scenario

MAPE_i MAPE of the corresponding scenario



OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 09 September 2022

ACCEPTED 26 September 2022

PUBLISHED 09 January 2023

CITATION

Zhu J, Yin H, Ma Y, Sui B, Wang M and
Yang K (2023), Opinions on unbalanced
funds in China's electricity market.
Front. Energy Res. 10:1040451.
doi: 10.3389/fenrg.2022.1040451

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Opinions on unbalanced funds in China's electricity market

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KEYWORDS

electricity market, spot market, unbalanced funds, dual-track mechanism, market
settlement

Introduction

In 2017, the construction of the spot market was started under the new round reform of China's electricity market. Eight provinces (i.e., Shanxi, Zhejiang, Guangdong, Sichuan, West Inner Mongolia, Shandong, Fujian, and Gansu) were selected by the National Development and Reform Commission (NDRC) as the first batch of spot market trial operation areas (Cai et al., 2020). After that, each province conducted multiple rounds of continuous settlement trial operations. Unbalanced funds are inevitable in the process of the transaction and settlement in the electricity market. Various provinces have also experienced the problem of unbalanced funds during the settlement period. The power grid company does not profit or lose from the market. If the spot market does not apportion the unbalanced funds reasonable, there will produce enormous unbalanced funds in the sustaining operation of the market. When the gap between revenue and expenditure of the power grid company is in the red, the power grid company needs to pay this part of the cost, and then recover the cost from the market entities that generate this part of the unbalanced funds. Therefore, various market entities may obtain extra profits or bear losses from the market in an active or passive situation, which is not in line with the principle of fairness and justice in the market economy and is not conducive to the long-term and healthy development of the spot market. For example, from 16 May 2020 to 19 May 2020 during the trial operation of the spot market in Shandong Province, the unbalanced funds in the third continuous settlement were generated as high as 95.08 million RMB (Fu et al., 2022). This phenomenon has aroused the extensive attention of experts in the industry and has not been effectively solved so far. Therefore, exploring the causes and the solutions of unbalanced funds has an important significance.

Unbalanced funds in foreign electricity markets (Dannecker, 2015; The European Network of Transmission System Operators for Electricity, 2021) generally include settlement deviation fees, metering deviation fees, rounding fees, costs and fines due to company bankruptcy or other reasons (Long et al., 2019; He et al., 2021). These unbalanced funds are usually small. China's economic system includes both a command economic system in which the government determines the allocation of resources and a market economic system in which resources are allocated by buyers and sellers. These two jointly decide the particularity of China's electricity market. Therefore, in addition to the above-mentioned fees such as rounding fees. Unbalanced funds in China's electricity market also include planned unbalanced funds, congestion costs, compensation costs, deviation recovery fees etc. At

present, the problem of unbalanced funds in China's electricity market is generally believed to be caused by the dual-track operation of China's command and market economic system (Cui et al., 2021; Liu et al., 2021). It is also the only way to go through the reform process of electricity marketization. In the study of the problem of unbalanced funds, Wu et al. (2020a) believed that there were three kinds of settlement modes in the spot market based on the command and market economic system, and analyzed the settlement problem of unbalanced funds caused by the command economy. Gong et al. (2021) argued that government-mandated contracts can directly affect unbalanced funds. Based on the load forecasting techniques and spot electricity prices, a contract decomposition method was proposed. This method can ensure the fairness of contract decomposition and reduce the unbalanced funds by introducing a fairness coefficient. According to China's two dual-track operation modes of decoupling mode and coupling mode in the spot market. Wu et al. (2020b) considered that the coupling mode is more in line with the Chinese electricity market, and studied the settlement mechanism of the spot market and medium and long-term market based on this mode. Xu et al. (2021) established an agent-based model of the real-time balanced market considering unbalanced costs, and proposed methods such as the mechanism of unbalanced electricity price to reduce unbalanced funds. Based on the balance settlement mechanism of China's electricity market, Wu et al. (2020c) designed a balancing market clearing model for wind power participation. According to the market settlement rules, Lu et al. (2021) proposed to reduce the deviation settlement cost by controlling the energy storage equipment, thereby improving the operation efficiency of the retailer in the spot market. At present, scholars have carried out extensive research on unbalanced funds. However, many studies focused on how to reduce or allocate unbalanced funds. There is still a lack of relevant research on how to analyze the solution to the dual-track unbalanced funds based on the actual settlement rules of transactions in the spot market trial operation provinces.

Unbalanced funds

The remaining funds or arrears that are generated during the operation of the electricity market are often referred to as unbalanced funds. These funds usually cannot find the exact beneficiary. The generation mechanism of various unbalanced funds is different, which can generally be summarized as the mismatch between the electric quantity and prices on the power generation side (PGS) and the power consumption side (PCS). The trading rules in various pilot provinces are not identical, and there is no uniform definition of unbalanced funds. Each pilot province has also included all types of expenses into the category of unbalanced funds management. On the basis of the actual situation of China's electricity market, the unbalanced funds can be divided into dual-track unbalanced funds, congestion costs, compensation costs, deviation recovery fees, assessment fees (Yu

et al., 2020; Li et al., 2021) etc. Considering that the latter types of funds are different from the dual-track unbalanced funds and are all reflected in the market settlement, this article collectively refers to them as settlement unbalanced funds. The reason for dual-track unbalanced funds in China's electricity market is shown in Figure 1.

In China's dual-track electricity market with command and market, the generators on the PGS are divided into market-oriented power sources and priority power generation sources. Electricity users are divided into market-oriented users and priority electricity purchasers. Priority electricity purchasers refer to agricultural users and other small users who purchase electricity depend on power grid companies. All of them do not directly participate in the spot market. The liberalization proportion of the market scale on the PGS and the PCS is inconsistent. The electricity between priority electricity production and priority electricity purchasers is generally not equal. If the actual electricity usage of priority electricity purchasers is greater than the medium and long-term contract, the grid company needs to buy the market power and sell it to priority electricity purchasers. On the contrary, the grid company needs to buy scheduled contract energy and sell it to the market users. To achieve the balance of power grid electricity, it is necessary to adjust the units to achieve power balance. Under the command economy, the units with adjustment ability can provide adjustment ability for free. But under the market economy, market-oriented units are guided by price signals in the market. They are under no obligation to provide adjustment services for others free of charge. If generator units continue to provide balancing services for priority purchase and priority generation, they need to receive corresponding fees, but non-market users do not pay these fees. All of the above reasons will lead to the unbalance of revenue and expenditure in the system during the settlement process, and the resulting unbalanced funds are called dual-track unbalanced funds.

In addition to the dual-track unbalanced funds, there are several other types of unbalanced fees in the electricity market. Such as congestion costs, compensation costs, deviation recovery fees, assessment fees, and other fees. Although there are many types of these fees, they account for a small proportion of the unbalanced funds. These fees all lead to an unbalance in the overall revenue and expenditure of the system, and we collectively refer to them as settlement unbalance funds. The settlement unbalanced funds are closely related to the settlement rules of the electricity market.

Discussion

The dual-track operation mechanism of command and market is a major feature in China. This is also the transit point for China's electricity market to transform from a command economic system to a market economy system. At present, the reform of the electricity market in China has stepped into the acceleration period, and whether the problem of

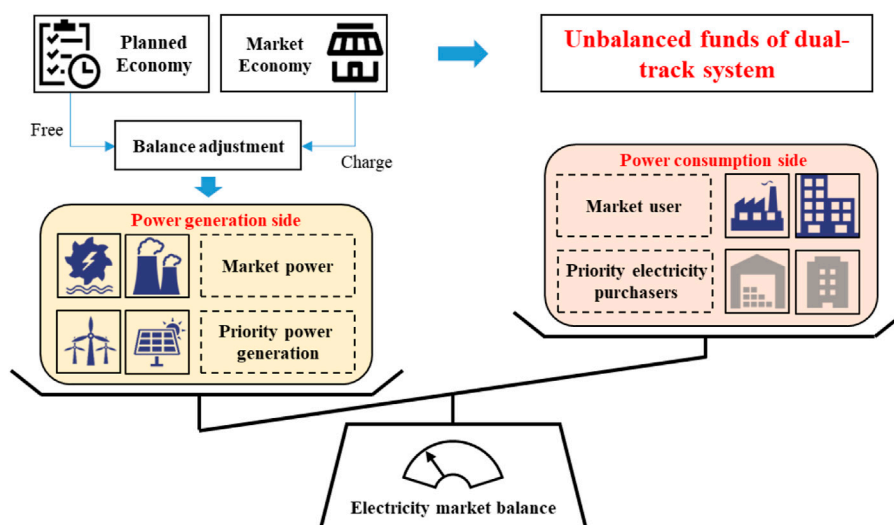


FIGURE 1
The unbalanced funds of dual-track system.

unbalanced funds can be properly resolved will also be one of the key factors for the success of the construction. This study will give some advice on how to solve the problem of unbalanced funds from the aspects of market mechanism and technical methods.

Market mechanism

The settlement mechanism of the electricity market should be further improved. Each pilot province should establish flexible and diverse market settlement methods according to its actual situation. For example, a settlement method in Guangdong Province is the decoupling of the planned electricity and the market electricity. This settlement method matches the priority power generation output curve according to the electricity consumption curve of the priority electricity purchase users. This method can reduce the unbalanced electricity in each period in the settlement, thereby reducing the dual-track unbalanced funds. Another example is the West Inner Mongolia electricity market. They change the “dual-track system” into a “single-track system,” allowing all market players on the PGS and PCS to participate in the electricity market on an equal footing. This helps them eliminate the risk of unbalanced funds. In addition, the fixed contract mechanism of Singapore and the self-dispatching mechanism of the PJM electricity market also provide another way of thinking for the settlement of unbalanced funds in China’s electricity market.

Based on the regulation of “who benefits, who bears,” the source of unbalanced funds should be clarified, and a fair and reasonable mechanism for the apportionment and return of unbalanced funds should be established. Whoever generates the unbalanced funds and who benefits from them should

bear the burden. For example, the calculation and apportionment method of unbalanced funds was clearly stipulated in the settlement rules of the electricity spot market in Gansu Province. On the basis of the ratio of the electricity consumption of the monthly non-spot market user and the spot market user, the unbalanced funds of the regional price difference are apportioned on the PGS and the PCS.

The policies of priority electricity generation and priority electricity consumption should be gradually integrated and connected with the market mechanism. Gradually realize the non-market electricity directly participate in the market, such as inter-provincial electricity, renewable energy and nuclear power. Through capacity guarantee mechanism replace the reduced base electricity. Steady push forwards the reform of the electricity market. The dual-track unbalanced funds are mainly affected by the fluctuation of the base electricity. Therefore, promoting the direct participation of non-market electricity in the market can effectively reduce the dual-track unbalanced funds, and the capacity guarantee mechanism can ensure a stable supply of base electricity. In 2021, the NDRC issued a notice about deepening the market reform of net prices for coal-fired power generation. The notice stipulates that all coal-fired power should participate in the electricity market by principle. This reduces the unbalanced funds to a certain extent.

Technical method

Grid transmission capacity needs to be further improved. The essence of congestion cost is the cost of transmission congestion due to insufficient grid transmission capacity. Therefore, by improving the power transmission capacity of

the power grid, or adopting congestion management methods such as the re-dispatch method and transaction reduction method, the occurrence of network congestion can be reduced. All of these methods can reduce the unbalanced funds in settlement caused by transmission congestion to a certain extent.

Medium and long-term electricity transactions need to be carried out with curves, and the accuracy of medium and long-term load forecasting needs to be improved. When conducting electricity transactions, market players should independently agree on the power load curve or the formation method of it, to guarantee the power load curves on the PGS are in line with the power load curves on the PCS. In this way, medium and long-term contracts can be delivered timely and completely, thereby reducing the deviation of the actual power generation and power consumption of market entities from the contract decomposition curve, and reducing the unbalanced funds during the settlement period generated by the deviation of electricity.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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Funding

This Project was supported by Science and Technology Foundation of SGCC (SGHAYY00SJS2200002).

Conflict of interest

JZ, HY, YM, BS, and MW were employed by Henan Power Exchange Center Co., Ltd.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 02 September 2022
ACCEPTED 20 September 2022
PUBLISHED 09 January 2023

CITATION
Xuan J, Chen Z, Zheng J, Zhang Z and
Shi Y (2023), Optimal planning of hybrid
electric-hydrogen energy storage
systems via multi-objective particle
swarm optimization.
Front. Energy Res. 10:1034985.
doi: 10.3389/fenrg.2022.1034985

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Optimal planning of hybrid electric-hydrogen energy storage systems via multi-objective particle swarm optimization

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Abstract: In recent years, hydrogen is rapidly developing because it is environmentally friendly and sustainable. In this case, hydrogen energy storage systems (HESSs) can be widely used in the distribution network. The application of hybrid electric-hydrogen energy storage systems can solve the adverse effects caused by renewable energy access to the distribution network. In order to ensure the rationality and effectiveness of energy storage systems (ESSs) configuration, economic indicators of battery energy storage systems (BESSs) and hydrogen energy storage systems, power loss, and voltage fluctuation are chosen as the fitness function in this paper. Meanwhile, multi-objective particle swarm optimization (MOPSO) is used to solve Pareto non-dominated set of energy storage systems' optimal configuration scheme, in which the technique for order preference by similarity to ideal solution (TOPSIS) based on information entropy weight (IEW) is used to select the optimal solution in Pareto non-dominated solution set. Based on the extended IEEE-33 system and IEEE-69 system, the rationality of energy storage systems configuration scheme under 20% and 35% renewable energy penetration rate is analyzed. The simulation results show that the power loss can be reduced by 7.9%–22.8% and the voltage fluctuation can be reduced by 40.0%–71% when the renewable energy penetration rate is 20% and 35% respectively in IEEE-33 and 69 nodes systems. Therefore, it can be concluded that the locations and capacities of energy storage systems obtained by multi-objective particle swarm optimization can improve the distribution network stability and economy after accessing renewable generation.

KEYWORDS

battery energy storage systems (BESSs), hydrogen energy storage systems (HESSs), multiple-objective particle swarm optimization (MOPSO), smart grid, voltage adjustment

Introduction

With the continuous advancement of science and technology in the world, the demand for energy supply is rising. Traditional energy based on fossil energy is facing major problems of resource depletion and environmental pollution (Li et al., 2022a), (Zhang et al., 2022). Developing clean and renewable energy, reducing the use of fossil energy, and reducing carbon emissions have become necessary means for the sustainable development of human society (Yang et al., 2020), (Yang et al., 2021a). However, renewable energy power generation is easily affected by weather factors, resulting in a series of problems such as voltage over-limit, large voltage fluctuation of distribution network, poor stability of power grid. With the development of energy storage systems (ESSs), configuring ESSs in distribution networks with a high penetration rate of renewable energy can effectively solve the above problems (Yang et al., 2021b; Yang, 2021; Wang et al., 2022).

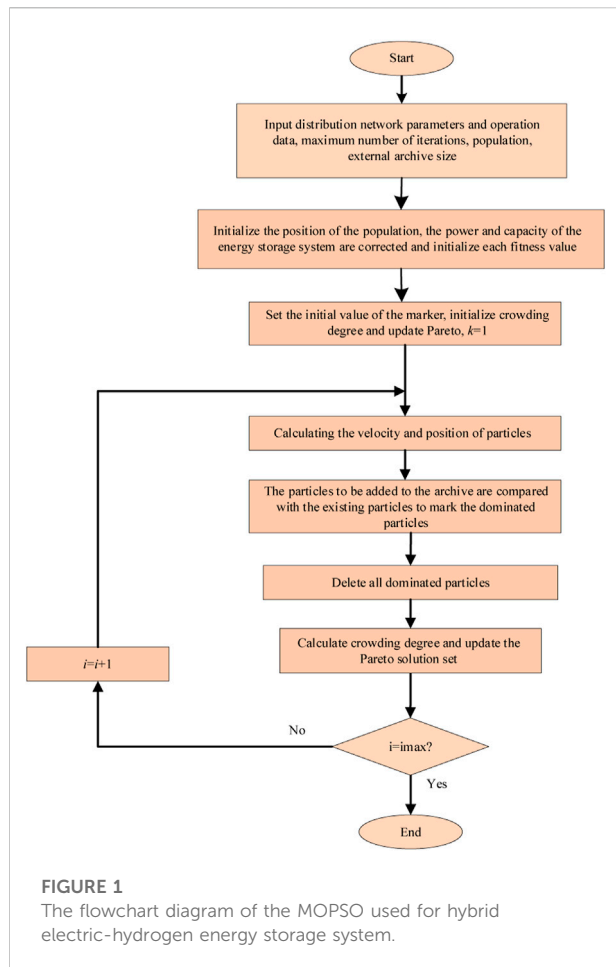
The ESSs can store the energy that cannot be consumed in the power grid, and when the power grid load increases and the power supply is insufficient, the stored energy is fed back to the power grid. Reference (Li et al., 2022b) established a flywheel energy storage system to assist the thermal power units in the power grid to participate in the primary frequency regulation of the power grid to improve the frequency stability of the power grid. However, the flywheel energy storage system is a device that uses the mechanical energy in the rotation of the flywheel to store energy. The device is usually very large and the charging and discharging time is short. This characteristic makes the flywheel energy storage system unsuitable for long-term energy storage and difficult to apply to the power grid. Hydrogen energy storage systems (HESSs) are chemical energy storage systems that use hydrogen as a storage medium and can store a large amount of energy by electrolysis of water to produce hydrogen. When the grid load increases, hydrogen can be converted into electrical energy through a fuel cell (FC) to supply power to the grid. Because of the high cleanliness and sustainability of hydrogen, HESSs are configured reasonably can accelerate the realization of low-carbon power grids and the goal of sustainable development.

In recent years, worldwide scholars have completed numerous research on ESSs configuration method (Sarvesh and Geena, 2017; Xing et al., 2017; Zhang et al., 2020; Georgious et al., 2021; Li et al., 2022c). In reference (Cui et al., 2017), aiming at minimizing the sum of voltage over-limit of each node, genetic algorithm was used to optimize the capacity of battery energy storage systems (BESSs). In reference (Yan et al., 2013), the annual net revenue was taken as the objective function to establish BESSs optimization value evaluation model, and the particle swarm optimization algorithm combined with multi-SUMT function was used to solve it. The models of ESSs optimization established in the above references are all single-objective models. The disadvantage of the single-objective model is that it is difficult

to fully consider the economy and grid stability in the process of ESSs configuration. Reference (Yan et al., 2022) studied the configuration method of the hybrid energy storage system of electrochemical energy storage and hydrogen energy storage, aiming at reducing the wind and solar curtailment rate of the system, using a two-level optimization mode, and solving the model by the proximal policy optimization algorithm. Reference (Jiang and Chen, 2021) used the improved artificial bee colony algorithm to study how to reduce the daily cost of users, reduce the energy loss of ESSs and reduce the fluctuation of wind and solar energy for the ESSs in microgrid system. In reference (Fu et al., 2022), the mathematical model of optimal configuration of ESSs is constructed with the goal of the economic benefit of ESSs and the influence of the energy storage device on the voltage quality of the distribution network. The objectives in the above research content are difficult to fully reflect the real situation of distribution network operation after ESSs are connected. In reference (Li et al., 2022d), a power interaction constraint model was introduced into the capacity optimal configuration model of the hybrid electric-hydrogen energy storage systems to configure the capacity of ESSs to improve system economy and power supply reliability. Reference (Xiang et al., 2015) established a hybrid optimization model for the configuration of BESSs intending to maximize the net profit in the whole life cycle of BESSs in the distribution network. In reference (Luo and Shen, 2022), a hybrid electric-hydrogen energy storage structure was proposed to deal with the economic and practical problems of wind/photovoltaic/storage microgrid. The model of ESS is established with the goal of life cycle cost. Through simulation analysis, it is proved that the hybrid energy storage structure has the characteristics of good economy, high reliability and environmental friendliness. In reference (Guo et al., 2022a) A bi-level programming model of lead-acid battery-supercapacitor hybrid energy storage system is proposed. The outer objective function is the annual return rate of energy storage investment, considering the income of energy storage system, life cycle cost and other factors. The inner objective function is the daily scheduling income of energy storage. The two-layer model is solved by particle swarm algorithm and CPLEX solvers. Reference (Guo et al., 2022b) optimized the capacity of the ESSs according to the economic index of distributed energy storage systems (DESSs). When optimizing the ESSs, the above research does not consider the influence of ESSs on the stability of the distribution network operation.

Based on the existing research content, considering that the configuration of ESSs needs to be determined from various angles. In this paper, a multi-objective particle swarm optimization (MOPSO) algorithm is proposed to optimize the configuration of hybrid electric-hydrogen energy storage systems when the penetration rate of renewable energy is 20% and 35% respectively. A multi-objective optimization model is established with the economic indicators of BESSs and HESSs, network loss, and voltage fluctuation as the objectives.

The main contributions of this work are:



- 1) A multi-objective optimization model based on Pareto is established, and a multi-objective location and capacity model of the hybrid energy storage system is established with three objectives;
- 2) TOPSIS based on IEW to establish weight is used to obtain the optimal solution from the Pareto front of MOPSO.
- 3) The extended IEEE-33 node systems and IEEE-69 node systems are simulated and tested when the renewable energy penetration rate is 20% and 35% respectively. In this way, the optimization ability of the MOPSO algorithm is verified, and the optimal configuration scheme of hybrid electric-hydrogen energy storage systems under two different node systems is obtained.

Battery energy storage systems/ hydrogen energy storage systems configuration model

The model consists of load, BESSs, photovoltaic power generation, wind power generation, electrolytic cell,

TABLE 1 MOPSO parameter setting.

Parameters	Value
c_1	1.6
c_2	1.6
w_{max}	0.9
w_{min}	0.4
n	50
k_{max}	150

TABLE 2 Main parameters of power grid.

Parameters of power grid	Value
System base capacity	10MVA
Total load power	(3.715 + j2.3) MVA
Wind power No. 1, No. 2 and No. 3 active power	1.2 MW
Photovoltaic No. 1 Active Power	2.5 MW

FC unit, and hydrogen tank (HT). The state of charge (SOC) of BESSs is an important parameter of charge and discharge operation.

The SOC of BESSs can be calculated as follows:

$$\begin{cases} \text{SOC}_i(t) = (1 - \delta \cdot \Delta t) \cdot \text{SOC}_i(t-1) + \left(\frac{P_{\text{cha},i}(t)}{\eta_{\text{cha},i}} \right) \cdot \Delta t, \text{ charging} \\ \text{SOC}_i(t) = (1 - \delta \cdot \Delta t) \cdot \text{SOC}_i(t-1) - \left(\frac{P_{\text{dis},i}(t)}{\eta_{\text{dis},i}} \right) \cdot \Delta t, \text{ discharging} \end{cases} \quad (1)$$

where $P_{\text{cha},i}(t)$ and $P_{\text{dis},i}(t)$ represent the charging and discharging power of node i in the period t ; $\eta_{\text{cha},i}$ and $\eta_{\text{dis},i}$ represent the charging and discharging efficiency of node i in the period t .

The exchange power between BESSs and the power grid can be calculated by Eq. 2:

$$P_{\text{grid},i}(t) = P_{\text{cha},i}(t) - P_{\text{dis},i}(t) \quad (2)$$

It should be noted that the charging and discharging processing of BESSs cannot proceed at the same time, so the power exchange between BESSs and network must be satisfied:

$$P_{\text{cha},i}(t) \cdot P_{\text{dis},i}(t) = 0 \quad (3)$$

Objective function

In this work, the economic index of the hybrid electric-hydrogen energy storage system, the daily network loss of the power grid, and voltage fluctuation is taken as the objectives, and

TABLE 3 Parameters of the IEEE-33 node system.

Node	Node	Resistance	Reactance	Susceptance	RateA	RateB	RateC	Ratio	Angle	Status	Ang _{min}	Ang _{max}
1	2	0.023947	0.035034	0.005438	9	0	0	0	0	1	-360	360
2	3	0.019502	0.028532	0.004429	9	0	0	0	0	1	-360	360
3	4	0.034443	0.05039	0.007822	9	0	0	0	0	1	-360	360
4	5	0.016846	0.024646	0.003826	9	0	0	0	0	1	-360	360
5	6	0.024331	0.035596	0.005526	9	0	0	0	0	1	-360	360
6	7	0.026067	0.038136	0.00592	9	0	0	0	0	1	-360	360
7	8	0.020457	0.029929	0.004646	9	0	0	0	0	1	-360	360
8	9	0.012716	0.018603	0.002888	9	0	0	0	0	1	-360	360
9	10	0.016852	0.024654	0.003827	9	0	0	0	0	1	-360	360
10	11	0.025991	0.038025	0.005903	9	0	0	0	0	1	-360	360
11	12	0.023079	0.033764	0.005241	9	0	0	0	0	1	-360	360
12	13	0.029865	0.043692	0.006782	9	0	0	0	0	1	-360	360
13	14	0.021867	0.031991	0.004966	9	0	0	0	0	1	-360	360
14	15	0.0239	0.034966	0.005428	9	0	0	0	0	1	-360	360
15	16	0.036016	0.052691	0.008179	9	0	0	0	0	1	-360	360
16	17	0.032137	0.047016	0.007298	9	0	0	0	0	1	-360	360
17	18	0.034804	0.050919	0.007904	9	0	0	0	0	1	-360	360
2	19	0.030902	0.045209	0.007018	9	0	0	0	0	1	-360	360
19	20	0.02796	0.040905	0.00635	9	0	0	0	0	1	-360	360
20	21	0.017597	0.025745	0.003996	9	0	0	0	0	1	-360	360
21	22	0.022385	0.03275	0.005084	9	0	0	0	0	1	-360	360
3	23	0.025339	0.037071	0.005755	9	0	0	0	0	1	-360	360
23	24	0.015075	0.022055	0.003424	9	0	0	0	0	1	-360	360
24	25	0.006635	0.009707	0.001507	9	0	0	0	0	1	-360	360
6	26	0.021343	0.031224	0.004847	9	0	0	0	0	1	-360	360
26	27	0.014976	0.02191	0.003401	9	0	0	0	0	1	-360	360
27	28	0.020055	0.029341	0.004555	9	0	0	0	0	1	-360	360
28	29	0.01193	0.017453	0.002709	9	0	0	0	0	1	-360	360
29	30	0.006367	0.009315	0.001446	9	0	0	0	0	1	-360	360
30	31	0.011941	0.01747	0.002712	9	0	0	0	0	1	-360	360
31	32	0.016817	0.024603	0.003819	9	0	0	0	0	1	-360	360
32	33	0.007963	0.01165	0.001808	9	0	0	0	0	1	-360	360

a multi-objective optimization model based on Pareto can be established as follows:

$$\begin{cases} \min F(\mathbf{x}) = \min \{F_1, F_2, F_3\} \\ \text{s.t. } H(\mathbf{x}) \leq 0 \end{cases} \quad (4)$$

where $F(\mathbf{x})$ consists of objective functions $\{F_1, F_2, F_3\}$, which are the economic index of BESSs and HESSs, daily network loss, and voltage fluctuation respectively; $\mathbf{x}$ represents the decision space consisting of the optimal installation node location, capacity, and hourly power optimization variables of BESSs and HESSs; $H(\mathbf{x})$ represents the constraints.

1) Economic indicators of ESSs

ESSs economic indicators include total capital cost (TCC) and maintenance cost (MC). The economic indicators of HESSs and BESSs are as follows:

$$\min F_1 = TCC_B + MC_B + TCC_H + MC_H \quad (5)$$

Total capital cost of battery energy storage systems

$$TCC_B = \mu_{CRF, B} \cdot \sum_{i=1}^{N_{BESS}} (c_{bat} + c_{EPC, B} - I_{sub, B}) \cdot E_{BESS, i} \quad (6)$$

TABLE 4 Parameters of the IEEE-69 node system.

Node	Node	Resistance	Reactance	Susceptance	RateA	RateB	RateC	Ratio	Angle	Status	Ang _{min}	Ang _{max}
1	2	0.005	0.0012	0	10	10	10	0	0	1	−360	360
2	3	0.005	0.0012	0	10	10	10	0	0	1	−360	360
3	4	0.0015	0.0036	0	10	10	10	0	0	1	−360	360
4	5	0.0251	0.0294	0	10	10	10	0	0	1	−360	360
5	6	0.366	0.1864	0	10	10	10	0	0	1	−360	360
6	7	0.3811	0.1941	0	10	10	10	0	0	1	−360	360
7	8	0.0922	0.047	0	10	10	10	0	0	1	−360	360
8	9	0.0493	0.0251	0	10	10	10	0	0	1	−360	360
9	10	0.819	0.2707	0	10	10	10	0	0	1	−360	360
10	11	0.1872	0.0691	0	10	10	10	0	0	1	−360	360
11	12	0.7114	0.2351	0	10	10	10	0	0	1	−360	360
12	13	1.03	0.34	0	10	10	10	0	0	1	−360	360
13	14	1.044	0.345	0	10	10	10	0	0	1	−360	360
14	15	1.058	0.3496	0	10	10	10	0	0	1	−360	360
15	16	0.1966	0.065	0	10	10	10	0	0	1	−360	360
16	17	0.3744	0.1238	0	10	10	10	0	0	1	−360	360
17	18	0.0047	0.0016	0	10	10	10	0	0	1	−360	360
18	19	0.3276	0.1083	0	10	10	10	0	0	1	−360	360
19	20	0.2106	0.069	0	10	10	10	0	0	1	−360	360
20	21	0.3416	0.1129	0	10	10	10	0	0	1	−360	360
21	22	0.014	0.0046	0	10	10	10	0	0	1	−360	360
22	23	0.1591	0.0526	0	10	10	10	0	0	1	−360	360
23	24	0.3463	0.1145	0	10	10	10	0	0	1	−360	360
24	25	0.7488	0.2457	0	10	10	10	0	0	1	−360	360
25	26	0.3089	0.1021	0	10	10	10	0	0	1	−360	360
26	27	0.1732	0.0572	0	10	10	10	0	0	1	−360	360
27	28	0.0044	0.0108	0	10	10	10	0	0	1	−360	360
28	29	0.064	0.1565	0	10	10	10	0	0	1	−360	360
29	30	0.3978	0.1315	0	10	10	10	0	0	1	−360	360
30	31	0.0702	0.0232	0	10	10	10	0	0	1	−360	360
31	32	0.351	0.116	0	10	10	10	0	0	1	−360	360
32	33	0.839	0.2816	0	10	10	10	0	0	1	−360	360
33	34	1.708	0.5646	0	10	10	10	0	0	1	−360	360
34	35	1.474	0.4873	0	10	10	10	0	0	1	−360	360
3	36	0.0044	0.0108	0	10	10	10	0	0	1	−360	360
36	37	0.064	0.1565	0	10	10	10	0	0	1	−360	360
37	38	0.1053	0.123	0	10	10	10	0	0	1	−360	360
38	39	0.0304	0.0355	0	10	10	10	0	0	1	−360	360
39	40	0.0018	0.0021	0	10	10	10	0	0	1	−360	360
40	41	0.7288	0.8509	0	10	10	10	0	0	1	−360	360
41	42	0.31	0.3623	0	10	10	10	0	0	1	−360	360
42	43	0.041	0.0478	0	10	10	10	0	0	1	−360	360
43	44	0.0092	0.0116	0	10	10	10	0	0	1	−360	360
44	45	0.1089	0.1373	0	10	10	10	0	0	1	−360	360
45	46	0.0009	0.0012	0	10	10	10	0	0	1	−360	360
4	47	0.0034	0.0084	0	10	10	10	0	0	1	−360	360
47	48	0.0851	0.2083	0	10	10	10	0	0	1	−360	360
48	49	0.2898	0.7091	0	10	10	10	0	0	1	−360	360

(Continued on following page)

TABLE 4 (Continued) Parameters of the IEEE-69 node system.

Node	Node	Resistance	Reactance	Susceptance	RateA	RateB	RateC	Ratio	Angle	Status	Ang _{min}	Ang _{max}
49	50	0.0822	0.2011	0	10	10	10	0	0	1	-360	360
8	51	0.0928	0.0473	0	10	10	10	0	0	1	-360	360
51	52	0.3319	0.1114	0	10	10	10	0	0	1	-360	360
52	53	0.174	0.0886	0	10	10	10	0	0	1	-360	360
53	54	0.203	0.1034	0	10	10	10	0	0	1	-360	360
54	55	0.2842	0.1447	0	10	10	10	0	0	1	-360	360
55	56	0.2813	0.1433	0	10	10	10	0	0	1	-360	360
56	57	1.59	0.5337	0	10	10	10	0	0	1	-360	360
57	58	0.7837	0.263	0	10	10	10	0	0	1	-360	360
58	59	0.3042	0.1006	0	10	10	10	0	0	1	-360	360
59	60	0.3861	0.1172	0	10	10	10	0	0	1	-360	360
60	61	0.5075	0.2585	0	10	10	10	0	0	1	-360	360
61	62	0.0974	0.0496	0	10	10	10	0	0	1	-360	360
62	63	0.145	0.0738	0	10	10	10	0	0	1	-360	360
63	64	0.7105	0.3619	0	10	10	10	0	0	1	-360	360
64	65	1.041	0.5302	0	10	10	10	0	0	1	-360	360
11	66	0.2012	0.0611	0	10	10	10	0	0	1	-360	360
66	67	0.0047	0.0014	0	10	10	10	0	0	1	-360	360
12	68	0.7394	0.2444	0	10	10	10	0	0	1	-360	360
68	69	0.0047	0.0016	0	10	10	10	0	0	1	-360	360

where N_{BESS} represents the installation number of BESSs; c_{bat} represents the cost of a single battery; $c_{\text{EPC}, \text{B}}$ represents the engineering, procurement, and construction (EPC) cost of BESSs; $I_{\text{sub}, \text{B}}$ represents the government subsidy for BESSs; $E_{\text{BESS}, i}$ represents the capacity of the i th BESS; $\mu_{\text{CRF}, \text{B}}$ represents the capital recovery factor (CRF).

Maintenance cost of battery energy storage systems

$$\text{MC}_{\text{B}} = \sum_{i=1}^{N_{\text{BESS}}} c_{\text{FMC}, \text{B}} \cdot P_{\text{BESS}, i} \quad (7)$$

where $c_{\text{FMC}, \text{B}}$ represents the annual fixed MC of a single BESS; $P_{\text{BESS}, i}$ represents the power of the i th BESS.

Total capital cost of hydrogen energy storage systems

$$\begin{cases} \text{TCC}_{\text{H}} = \mu_{\text{CRF}, \text{H}} \cdot \sum_{i=1}^{N_{\text{HESS}}} (c_{\text{sys}, \text{H}i} + c_{\text{EPC}, \text{H}} - I_{\text{sub}, \text{H}} \cdot P_{\text{HESS}, i}) \\ c_{\text{sys}, \text{H}i} = (c_{\text{FC}} + c_{\text{E}}) \cdot P_{\text{HESS}, i} + c_{\text{HT}} \cdot Q_{\text{HT}, i} \end{cases} \quad (8)$$

where $\mu_{\text{CRF}, \text{H}}$ represents the cost recovery coefficient of HESSs; N_{HESS} represents the number of HESSs installed; c_{FC} and c_{E} are the cost of FC and electrolyzer respectively; c_{HT} and $Q_{\text{HT}, i}$ represent the cost and capacity of HT; $P_{\text{HESS}, i}$ represents the power of the i th HESS; $c_{\text{EPC}, \text{H}}$ represents the EPC cost of HESSs; $I_{\text{sub}, \text{H}}$ represents government subsidies for HESSs.

Maintenance cost of hydrogen energy storage systems

$$\text{MC}_{\text{H}} = \sum_{i=1}^{N_{\text{HESS}}} c_{\text{FMC}, \text{H}} \cdot P_{\text{HESS}, i} \quad (9)$$

where $c_{\text{FMC}, \text{H}}$ represents the annual fixed MC of a single HESS; $P_{\text{HESS}, i}$ represents the power of the i th HESS.

The power grid loss is considered in ESSs siting and sizing planning, expressed as daily power losses, as follows:

$$\min F_2 = \sum_{t=1}^T \sum_{i=1}^L (R_i I_i^2(t)) \quad (10)$$

where F_2 represents daily power losses; L represents the number of lines in the distribution network; R_i represents the resistance on the i th connection line; $I_i(t)$ is the current on the i th line at time t .

TABLE 5 Main parameters of BESSs and HESSs.

	Cost of a single battery	c_{bat}	209,000 dollars/MW·h
BESSs	EPC cost	$c_{EPC, B}$	123,000 dollars/MW·h, DT = 0.5 h
			245,000 dollars/MW·h, DT = 1 h
			392,000 dollars/MW h, DT = 2 h
			686,000 dollars/MW·h, DT = 4 h
	Annual fixed MC	$c_{FMC, B}$	20,000 dollars/MW
	Government subsidy	$I_{sub, B}$	90,000 dollars/MW·h
HESSs	Cost of electrolyzer	c_E	323,000 dollars/MW
	Cost of FC	c_{FC}	300 dollars/MW
	Cost of HT	c_{HT}	21 dollars/kg
	Annual fixed MC	$c_{FMC, H}$	80,000 dollars/MW
	Government subsidies	$I_{sub, H}$	120,000 dollars/MW·

The voltage quality of the power grid is considered in the location and capacity planning of the ESSs, expressed as daily voltage fluctuations, as follows:

$$\min F_3 = \sum_{i=1}^N \sum_{t=1}^T |V_i(t) - \bar{V}_i| \quad (11)$$

where F_3 represents daily voltage fluctuations; N represents the number of system nodes; $V_i(t)$ represents the voltage of i node at time t ; $\bar{V}_i$ represents the average voltage of i node in T period.

Constraints

$$U_i^{\min} \leq U_i(t) \leq U_i^{\max} \quad (12)$$

where $U_i(t)$ represents the node voltage of node i at time t ; $U_i^{\max}$ represents the node voltage upper limit of node i ; $U_i^{\min}$ represents the lower limit of node voltage of node i .

2) Charge-discharge constraints of BESSs and HESSs

$$\begin{cases} 0 \leq P_{cha, BESS_i}(t) \leq P_{BESS, i} \cdot \eta_{cha, BESS} \\ -P_{BESS, i} \cdot \eta_{dis, BESS} \leq P_{dis, BESS_i}(t) \leq 0 \end{cases} \quad (13)$$

$$\begin{cases} 0 \leq P_{cha, HESS_i}(t) \leq P_{HESS, i} \cdot \eta_{cha, HESS} \\ -P_{HESS, i} \cdot \eta_{dis, HESS} \leq P_{dis, HESS_i}(t) \leq 0 \end{cases} \quad (14)$$

Here, Eq. 13 represents the charge and discharge constraints of BESSs, where $P_{BESS, i}$ represents the power of the i th BESS; $P_{cha, BESS_i}(t)$ represents the charging power of the i th BESS at time t ; $\eta_{cha, BESS}$ and $\eta_{dis, BESS}$ represent the charge and discharge efficiency of BESSs, respectively. Eq. 14 represents the charge and discharge constraints of HESSs, where $P_{HESS, i}$ represents the power of the i th HESS; $P_{cha, HESS_i}(t)$ represents the charging

power of the i th HESS at time t ; $\eta_{cha, HESS}$ and $\eta_{dis, HESS}$ represent the charge and discharge efficiency of HESSs, respectively.

3) Capacity and power constraints of ESSs

$$\begin{cases} E_{BESS}^{\min} \leq E_{BESS} \leq E_{BESS}^{\max} \\ P_{BESS}^{\min} \leq P_{BESS} \leq P_{BESS}^{\max} \end{cases} \quad (15)$$

$$\begin{cases} E_{HESS}^{\min} \leq E_{HESS} \leq E_{HESS}^{\max} \\ P_{HESS}^{\min} \leq P_{HESS} \leq P_{HESS}^{\max} \end{cases} \quad (16)$$

where Eq. 15 represents the upper and lower limits of the capacity and power of BESSs; Eq. 16 represents the upper and lower limits of the capacity and power of HESSs.

4) Installation node number constraints of ESSs

$$\begin{cases} N_{BESS}^{\min} \leq N_{BESS} \leq N_{BESS}^{\max} \dots N_{ESS1} \neq N_{ESS2} \\ N_{HESS}^{\min} \leq N_{HESS} \leq N_{HESS}^{\max} \end{cases} \quad (17)$$

where Eq. 17 represents the upper and lower limits of installation node number of ESSs. It should be noted that since node 1 is a balanced node, the installation node number of BESSs and HESSs starts from node 2, and the two energy storage devices cannot be installed at the same node location.

$$SOC^{\min} \leq SOC(t) \leq SOC^{\max} \quad (18)$$

where $SOC^{\max}$ and $SOC^{\min}$ represent the upper and lower limits of SOC of BESSs, respectively. In this work, the $SOC^{\min}$ and $SOC^{\max}$ are set to 20% and 90%, respectively.

Model solution based on multi-objective particle swarm optimization

Multi-objective particle swarm optimization

In MOPSO, the swarm is composed of multiple particles, each particle represents a feasible solution of the optimization problem. The algorithm uses the global optimal solution and local optimal solution in each iteration to update the fitness. Eq. 19, 20 are the update methods of particle velocity and position (Shi and Wei, 2022).

$$v_i(t+1) = wv_i(t) + r_1c_1(Pbest_i(t) - x_i(t)) + r_2c_2(Gbest_i(t) - x_i(t)) \quad (19)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (20)$$

where $Pbest_i(t)$ represents the historical optimal position of the i ($i = 1, 2, 3, \dots, N$) particles in the search process, which is the local optimal solution; $Gbest_i(t)$ represents the optimal position of all particles in the current search results, which is global optimal solution; r_1 and r_2 represent random values in $[0,1]$; c_1 and c_2 represent particle self and group learning factors, usually

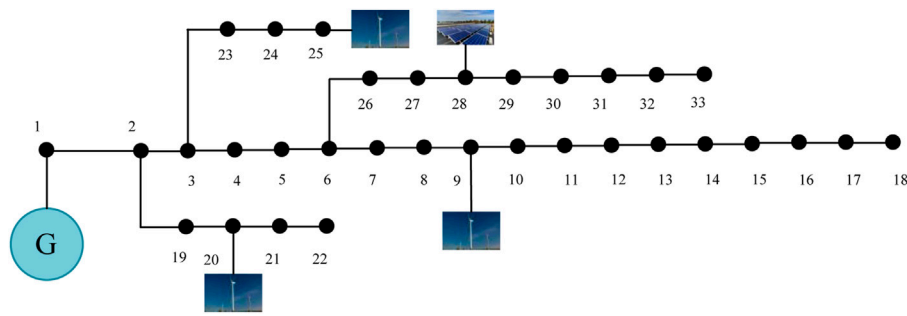


FIGURE 2
Topology of the extended IEEE-33 bus.

TABLE 6 Network loss and voltage fluctuation when ESS is not configured.

Renewable energy penetration rate (%)	No access to ESSs	
	Daily network loss/MW	Daily voltage fluctuation/p.u
20	1.39	5.917
35	1.213	5.598

between 0 and 2; w represents the value of the inertia weight that controls the particles in the population to search in the solution space, as follows:

$$w(t) = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} \times t \quad (21)$$

where $w_{\max}$ and $w_{\min}$ represents the maximum and the minimum inertia weight coefficient, respectively; $k_{\max}$ represents the maximum number of iterations.

The details of MOPSO are as follows:

- 1) Input distribution network parameters and operation data;
- 2) Set MOPSO parameters, population initialization, set the initial value of the marker;
- 3) Adding a new particle to the external archive set and marking the dominated particle by comparing it with the existing particle;
- 4) Delete all marked particles;
- 5) Calculate the current crowding degree according to Eq. 22, sort the crowding degree in descending order, and control the size of Pareto solution set;
- 6) The particles with the first 10% crowding degree are selected as the optimal particles;

- 7) Steps (3–6) are repeated to obtain the Pareto optimal solution set. The flowchart diagram of the MOPSO used for hybrid electric-hydrogen energy storage system is shown in [Figure 1](#).

Pareto solution set storage and selecting

It should be noted that the external archive set is used to store the Pareto solution set. During the iteration, the particles obtained from each iteration are compared with all the particles already in the archive to update the solution set in the archive. The specific methods are as follows:

- 1) The particles to be added are compared with all particles in the archive, and if the particles to be added dominate a particle in the archive, the particles in the archive are marked;
- 2) If a particle in the archive dominates the particles to be added, the particles to be added will be marked;
- 3) When all the particles are compared, delete all marked particles.

To ensure computational speed, the external archive can only store a limited number of solutions. Therefore, the size of the Pareto solution set is limited, and the crowding degree is used to limit the size of the Pareto solution set below the limit value. The crowding degree is calculated as follows:

$$n_d = [f_i(t+1) - f_i(t-1)] / ((f_i^{\max} - f_i^{\min})) \quad (22)$$

where, n_d represents the crowding degree of the population; $f_i^{\max}$ and $f_i^{\min}$ represent the maximum fitness value and the minimum fitness value of the i th population.

TABLE 7 BESSs and HESSs configuration schemes and optimization results under two different renewable energy penetration rates.

Renewable energy penetration rate (%)	BESSs optimal configuration scheme			HESSs optimal configuration scheme			Results		
	Node number of the configuration location	Capacity/MW·h	Power/MW	Node number of the configuration location	Capacity/kg	Power/MW	Cost of configuring ESSs/dollars	Daily network loss/MW	Daily voltage fluctuation/p.u
20	[7 26]	[0.7148 0.3615]	[0.7069 0.4526]	[11 10]	[12.349 7.420]	[0.7105 0.4669]	2.68e+05	1.1175	2.1215
35	[6 26]	[0.1886 0.5279]	[0.7112 0.6805]	[23 26]	[9.1354 8.32]	[0.6767 0.7139]	2.16e+05	0.9356	1.6228

Technique for order preference by similarity to ideal solution based on information entropy weight to establish weights

In this paper, a TOPSIS based on IEW is designed. The optimal solution in the Pareto solution set is taken as the optimal decision scheme, which is composed of the following steps (Zhang et al., 2018):

1) Dimensionless objective function

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad (23)$$

Eq. 24 represents the original data matrix consisting of n objective functions, each of which consists of m attributes.

$$f_{n,m} = \frac{-x_{n,(m-1)}}{x_{n,m} - x_{n,(m-1)}} \quad (24)$$

The normalized matrix F_{ij} after dimensionless is obtained from Eq. 25:

$$F = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1m} \\ f_{21} & f_{22} & \cdots & f_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \cdots & f_{nm} \end{bmatrix} \quad (25)$$

2) Calculating the entropy H_j and weight coefficient ω_j of each element in the normalized matrix

$$H_j = -\frac{1}{\ln n} \sum_{i=1}^n f_{ij} \ln f_{ij}, \quad (j = 1, 2, \dots, m) \quad (26)$$

$$\omega_j = \frac{1 - H_j}{\sum_{k=1}^m 1 - H_k}, \quad (j = 1, 2, \dots, m) \quad (27)$$

3) Calculating the distance between each objective function and the absolute ideal solution

$$D_i^+ = \sqrt{\sum_{j=1}^m \omega_j (F_j^+ - f_{ij})^2} \quad (28)$$

$$D_i^- = \sqrt{\sum_{j=1}^m \omega_j (F_j^- - f_{ij})^2} \quad (29)$$

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (30)$$

where D_i^+ represents the distance between the i th objective function and the absolutely positive ideal solution; D_i^- represents the distance between the i th objective function and the absolutely negative ideal solution; C_i represents the score of the i th objective function, which means that the larger the value of C_i , the closer it is to the optimal solution.

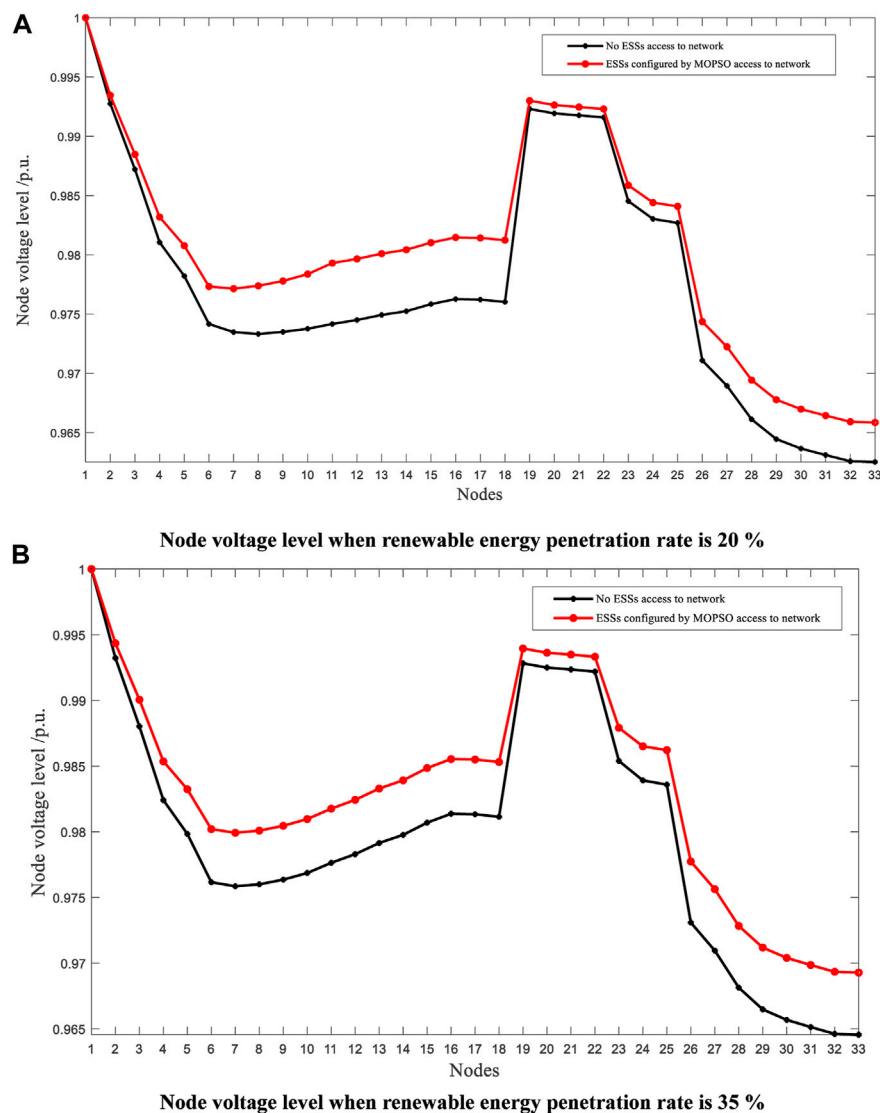


FIGURE 3

Node voltage level after optimized configuration of ESSs when renewable energy penetration is 20% and 35%. (A) Node voltage level when renewable energy penetration rate is 20 %; (B) Node voltage level when renewable energy penetration rate is 35 %.

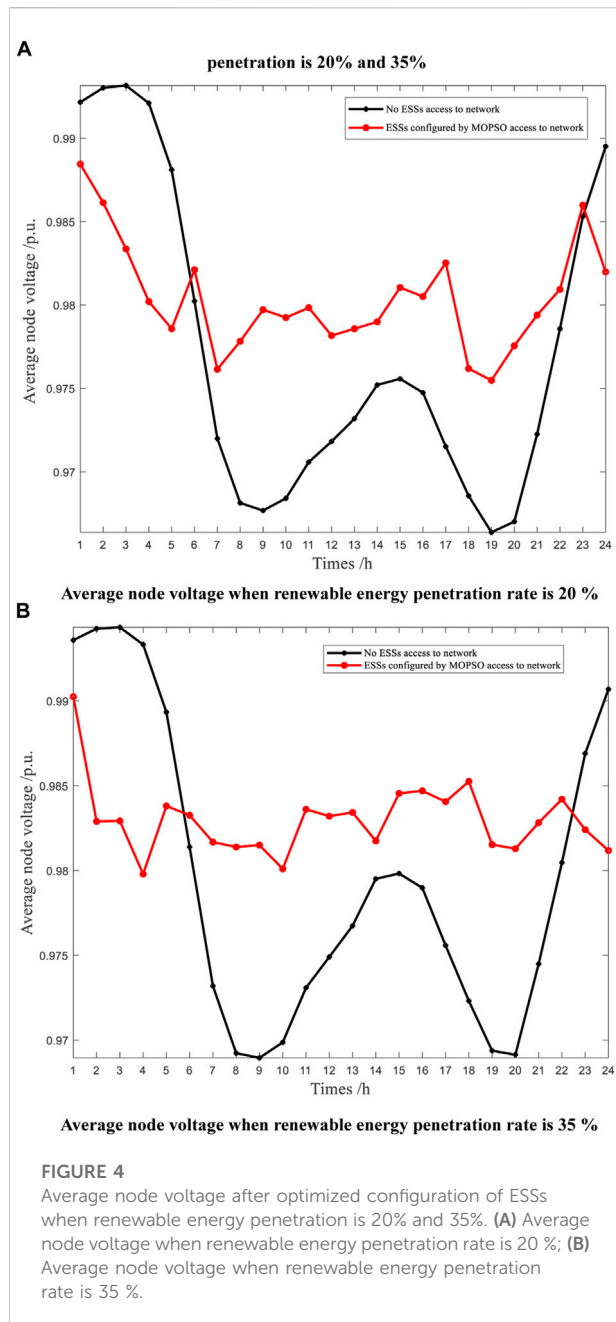
Case studies

In this work, the extended IEEE-33 and extended IEEE-69 node system are used to test whether the ESSs configured by MOPSO can improve the power quality, reduce the voltage fluctuation and improve the stability of the power system when the renewable energy penetration rate is 20% and 35% respectively. The parameter settings of MOPSO are shown in Table 1. Table 2 shows the main parameters of power grid (Yang et al., 2021c). Table 3 and Table 4 shows the parameters of the IEEE-33 node system and IEEE-69 node system. Table 5 shows the main parameters of BESSs and HESSs. Moreover, the longer the duration time (DT), the higher the battery cost.

Results analysis of extended IEEE-33 node system

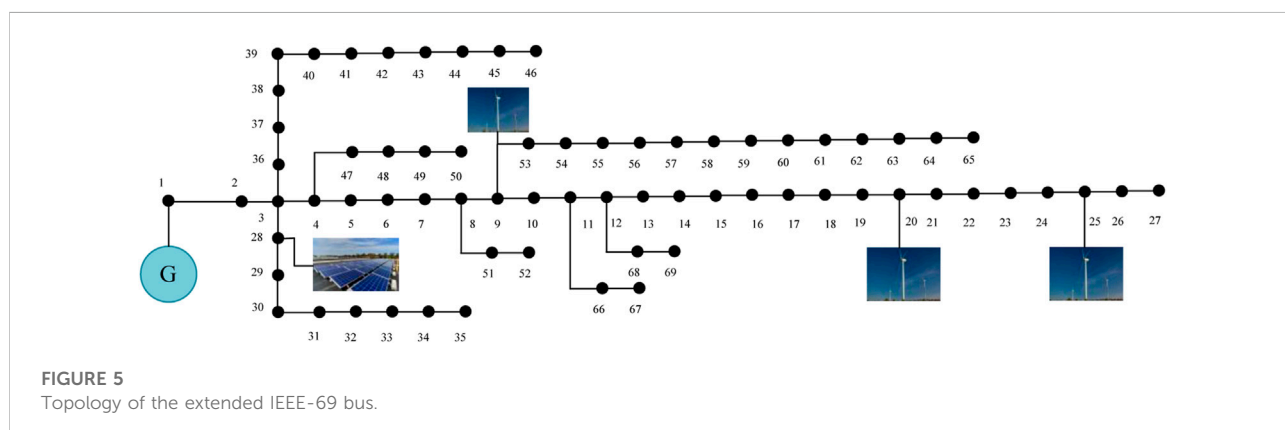
The topology of the extended IEEE-33 node system is shown in Figure 2. Wind power No. 1, No. 2 and No. 3 are connected at nodes 9, 20 and 25 respectively. Photovoltaic No. 1 is connected at nodes 28.

Table 6 shows the daily network loss and daily voltage fluctuation without ESSs. Table 7 shows the optimal configuration scheme of TOPSIS MOPSO based on IEW method under two different renewable energy penetration rates. By comparing Table 6 and Table 7, it can be found that the daily network loss of the power grid is reduced and the daily node voltage fluctuation is significantly reduced after the configuration of the hybrid electric-hydrogen energy storage system. When renewable energy



penetration rate is 20%, the daily network loss of the power grid decreases by 0.2725 MW, and the daily node voltage fluctuation decreases by 3.7955 p. u. When the renewable energy penetration rate is 35%, the daily network loss decreases 0.2774 MW, the daily node voltage fluctuation decreases 3.9752 p. u. It can be seen from Table 7 that when the renewable energy penetration rate is 20%, the two BESSs are installed at node seven and node 26 respectively, which capacities are 0.7148 MWh and 0.3615 MWh respectively. Meanwhile, the power capacity of 0.7069 MW and 0.4526 MW respectively. Two HESSs are installed in node 11 and node 10, with the capacity of 12.349 kg, 7.420 kg, and the power of 0.7105 MW, and 0.4669 MW respectively. When the rate is 35%, the two BESSs are installed at node six and node 26 respectively, and their capacities are 0.1886 MW h and 0.5279 MW h respectively, and their powers are 0.7112 MW and 0.6805 MW respectively. Two HESSs are installed in node 23 and node 26, with the capacity of 9.1354 kg, 8.32 kg, and the power of 0.6767 MW, and 0.7139 MW respectively. Moreover, when the renewable energy penetration generation rate is 20%, the total configuration cost of ESSs is \$ 268,000, which is \$ 52,000 higher than the rate is 35%. This can be confirmed by the total capacity of ESSs configurations for two different penetration rates. Figure 3A and Figure 3B show the node voltage levels of the extended IEEE-33 system after the optimized configuration of ESSs when the renewable energy penetration rate is 20% and 35%, respectively. Figure 4A and Figure 4B are the average node voltage of the IEEE-33 system after the optimized configuration of ESSs when the renewable energy penetration rate is 20% and 35%, respectively. A conclusion can be drawn from Figure 3 and Figure 4 that under two different renewable energy penetration rates, compared with the unconfigured hybrid electric-hydrogen energy storage system, the configuration of the hybrid electric-hydrogen energy storage system using the algorithm described in this work can improve the voltage level of the power grid, stabilize the average node voltage of the power grid, and improve the quality.

- 1) Node voltage level when renewable energy penetration rate is 20%
- 2) Node voltage level when renewable energy penetration rate is 35%
- 3) Average node voltage when renewable energy penetration rate is 20%
- 4) Average node voltage when renewable energy penetration rate is 35%



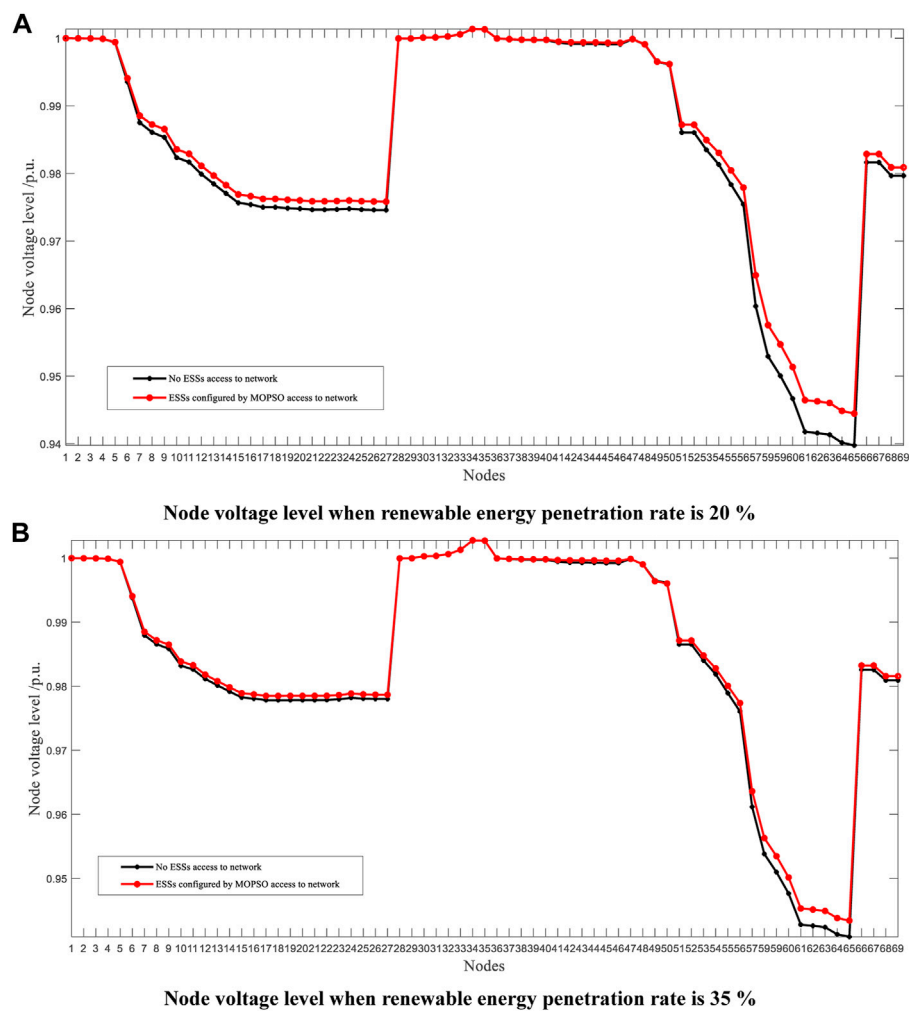


FIGURE 6

Node voltage level after optimized configuration of ESSs when renewable energy penetration is 20% and 35%. (A) Node voltage level when renewable energy penetration rate is 20 %; (B) Node voltage level when renewable energy penetration rate is 35 %.

Results analysis of extended IEEE-69 node system

The topology of the extended IEEE-69 node system is shown in Figure 5. Wind power No. 1, No. 2 and No. 3 are connected at nodes 9, 20 and 25 respectively. Photovoltaic No. 1 is connected at nodes 28.

Table 8 shows the daily network loss and daily voltage fluctuation without ESSs. Table 9 shows the optimal configuration scheme of TOPSIS MOPSO based on IEW method under two different renewable energy penetration rates. By comparing Table 8 and Table 9, it can be found that the hybrid electric-hydrogen energy storage system configured can reduce the daily network loss of the power grid and the daily node voltage fluctuation. When renewable energy penetration rate is 20%, the daily network loss of the power grid decreases by 0.2987 MW, and

the daily node voltage fluctuation decreases by 1.881 p. u. When the renewable energy penetration rate is 35%, the daily network loss decreases 0.1833 MW, the daily node voltage fluctuation decreases 2.2537 p. u. It can be seen from Table 9 that when the renewable energy penetration rate is 20%, the two BESSs are installed at node 57 and node 48 respectively, which capacities are 0.2428 MWh and 0.1528 MWh respectively. Meanwhile, the power of both BESSs is 0.72 MW. Two HESSs are installed in node 36 and node 2, with the capacity of 13 kg, and 14.338 kg, and the power of both HESSs is 0.72 MW. When the rate is 35%, the two BESSs are installed at node 57 and node 36 respectively, and their capacities are 0.5553 MWh and 0.1 MWh respectively, and their powers are 0.72 MW and 0.6621 MW respectively. Two HESSs are installed in node 49 and node 36, with the capacity of 6.2487 kg, 6.2345 kg, and the power of 0.6702 MW, and 0.6844 MW respectively. Furthermore, it can be seen from Table 9 that the total capacity of ESSs with 20% renewable

TABLE 8 Network loss and voltage fluctuation when ESSs is not configured.

Renewable energy penetration rate (%)	No access to ESSs	
	Daily network loss/MW	Daily voltage fluctuation/p.u
20	2.418	4.874
35	2.329	4.764

energy penetration is lower than the 35% renewable energy penetration. Therefore, with 20% renewable penetration, the total allocation of ESSs is reduced by \$8,000 compared to 35% penetration, which is a reasonable result. Figures 6A,B show the node voltage levels of the extended IEEE-69 system after the optimized configuration of ESSs when the renewable energy penetration rate is 20% and 35%, respectively. Figures 7A,B are the average node voltage of the extended IEEE-69 system after the optimized configuration of ESSs when the renewable energy penetration rate is 20% and 35%, respectively. A conclusion can be drawn from Figure 6 and Figure 7 that after ESS is configured, the voltage level is improved, the average node voltage stability of the nodes of the power grid is improved, the fluctuation is reduced, and the stability of the power grid is improved.

Conclusion

In this work, a Pareto multi-objective optimization model based on MOPSO is proposed to configure the hybrid energy storage system to improve the stability of distribution network operation. Firstly, it is proved that MOPSO can obtain the ESSs configuration scheme stably when the renewable energy penetration rate is 20% and 35% respectively, through the extended IEEE-33 and IEEE-69 system tests. Secondly, Figure 8 shows the Pareto front of MOPSO and the position of the optimal solution, which proves that MOPSO has a strong optimization effect. Finally, by comparing with the system without ESSs, it is proved that the ESSs configuration scheme obtained by this method can improve the node voltage level of the distribution network, reduce the node average voltage fluctuation of the distribution network, and prevent the voltage from exceeding the limit. It should be noted that as the penetration of renewable generation increases, the net-load fluctuation of the distribution network has increased, which will influence the stability of the electric power system and electric quality of the users. Hence, the rate capacity of BESSs has expanded, so the configuration costs may increase. It can be seen from the Tables 7 and 9, when the renewable energy penetration rate of IEEE-33 system is 20% and 35%, the daily power loss is reduced

TABLE 9 BESSs and HESSs configuration schemes and optimization results under two different renewable energy penetration rates.

Renewable energy penetration rate (%)	BESSs optimal configuration scheme			HESSs optimal configuration scheme			Results		
	Node number of the configuration location	Capacity/MW·h	Power/MW	Node number of the configuration location	Capacity/kg	Power/MW	Cost of configuring ESSs/dollars	Daily network loss/MW	Daily voltage fluctuation/p.u
20	[57 48]	[0.2428 0.1528]	[0.72 0.72]	[36 2]	[13 14.338]	[0.72 0.72]	2.55e+05	2.1193	2.9226
35	[57 36]	[0.5553 0.1]	[0.72 0.6621]	[49 36]	[6.2487 6.2345]	[0.6702 0.6844]	2.63e+05	2.1457	2.5103

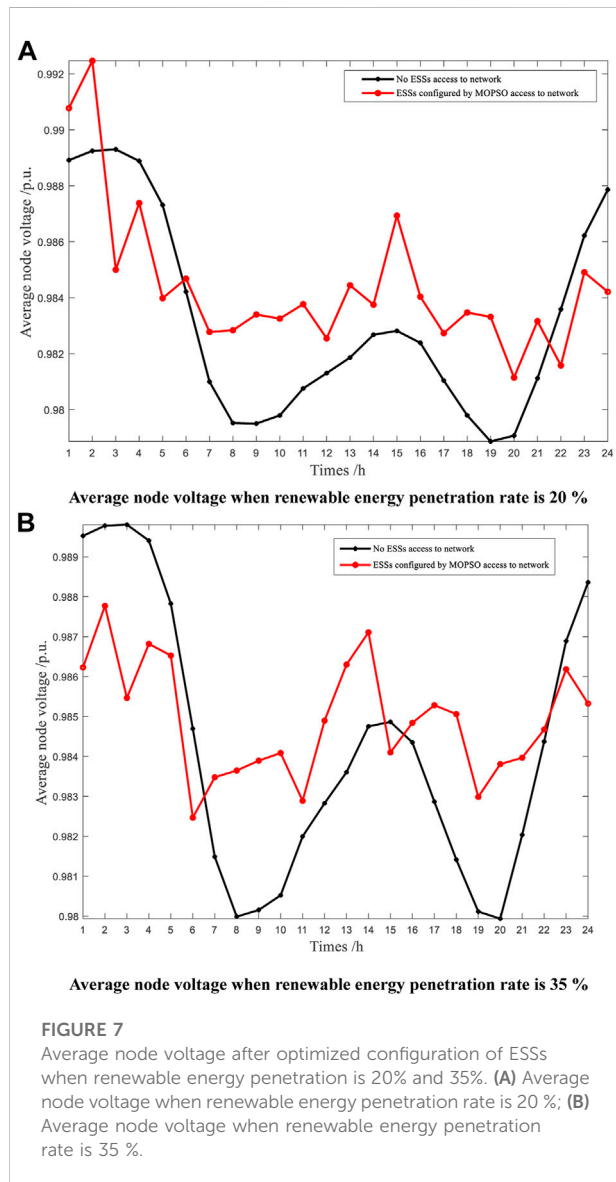


FIGURE 7

Average node voltage after optimized configuration of ESSs when renewable energy penetration is 20% and 35%. (A) Average node voltage when renewable energy penetration rate is 20 %; (B) Average node voltage when renewable energy penetration rate is 35 %.

by 0.2725 MW and 0.2774 MW respectively. At the same time, the daily node voltage fluctuation has decreased by 3.7955 p. u. and 3.9752 p. u. respectively. Furthermore, in IEEE-69 system, the daily power loss has reduced by 0.2987 MW and 0.1833 MW respectively as well as the daily node voltage fluctuation has decreased by 1.881 p. u. and 2.2537 p. u. respectively. It shows that ESSs configuration scheme based on MOPSO can improve the stability of the distribution network effectively.

- 1) Pareto distribution for IEEE-33 system with 20% penetration of renewable energy
- 2) Pareto distribution for IEEE-33 system with 35% penetration of renewable energy
- 3) Pareto distribution for IEEE-69 system with 20% penetration of renewable energy

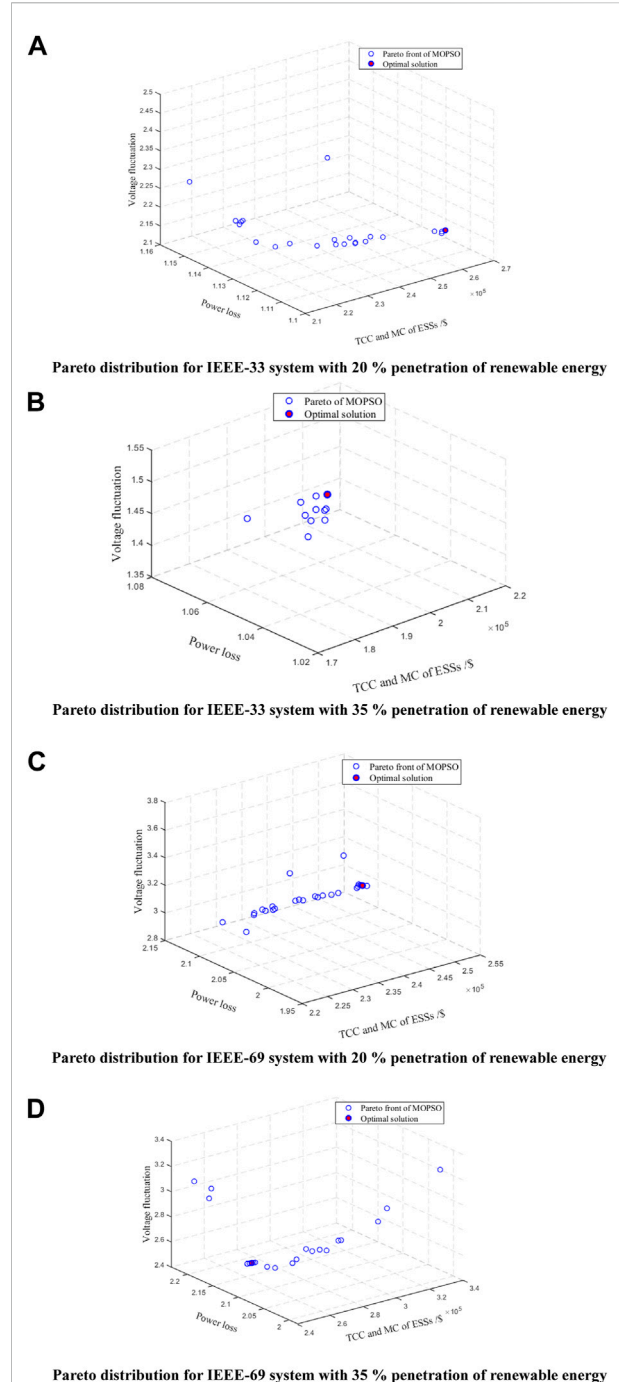


FIGURE 8

The pareto front of MOPSO and the position of the optimal solution. (A) Pareto distribution for IEEE-33 system with 20 % penetration of renewable energy; (B) Pareto distribution for IEEE-33 system with 35 % penetration of renewable energy; (C) Pareto distribution for IEEE-69 system with 20 % penetration of renewable energy; (D) Pareto distribution for IEEE-69 system with 35 % penetration of renewable energy.

- 4) Pareto distribution for IEEE-69 system with 35% penetration of renewable energy

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

JX: writing the manuscript; ZC: discussion of the economic index; JZ: discussion of the technology index; ZZ: editing; YS: discussion of the topic.

Funding

This work is funded by special research project of State Grid Fujian Electric Power Co., Ltd. (B3130N22000S).

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Conflict of interest

Author JX is employed by State Grid Fujian Electric Power Co., Ltd. Authors ZC, JZ, ZZ and YS are employed by Economic and Technological Research Institute of State Grid Fujian Electric Power Co., Ltd.

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OPEN ACCESS

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 28 August 2022
ACCEPTED 20 September 2022
PUBLISHED 09 January 2023

CITATION
Huang X, Tang B, Zhu M, Ma Y, Ma X,
Tang L, Wang X and Zhu D (2023), Like-
attracts-like optimizer-based video
robotics clustering control design for
power device monitoring
and inspection.
Front. Energy Res. 10:1030034.
doi: 10.3389/fenrg.2022.1030034

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Like-attracts-like optimizer-based video robotics clustering control design for power device monitoring and inspection

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A new meta-heuristic algorithm called like-attracts-like optimizer (LALO) is proposed in this article. It is inspired by the fact that an excellent person (i.e., a high-quality solution) easily attracts like-minded people to approach him or her. This LALO algorithm is an important inspiration for video robotics cluster control. First, the searching individuals are dynamically divided into multiple clusters by a growing neural gas network according to their positions, in which the topological relations between different clusters can also be determined. Second, each individual will approach a better individual from its superordinate cluster and the adjacent clusters. The performance of LALO is evaluated based on unimodal benchmark functions compared with various well-known meta-heuristic algorithms, which reveals that it is competitive for some optimizations.

KEYWORDS

like-attracts-like optimizer, meta-heuristic algorithm, growing neural gas network, dynamic clustering, video robotics cluster control

1 Introduction

Optimization is almost everywhere in our world, which usually attempts to find the perfect solution for a certain issue. To deal with these issues, various optimization methods have been proposed and have shown a good performance. Most of them fall into two categories: mathematical programming methods and meta-heuristics (Dai et al., 2009). The first type can rapidly converge to an optimum with high convergence stability by utilizing the gradient information (Guo et al., 2014), such as quadratic programming (Wang et al., 2014) and the Newton method (Kazemtabrizi and Acha, 2014). But the mathematical programming methods are highly dependent on the mathematical model of the optimization problem (Mirjalili and SCA, 2016). Furthermore, they are even incapable of addressing a blank-box optimization with only the input and output measurements. In contrast, the meta-heuristic algorithms are more flexible to be employed for different optimization problems since they are highly independent of the mathematical model of the specific problem (Zhang et al., 2017).

Furthermore, they are easily applied to an optimization with only the input and output measurements instead of any gradient information or convex transformation. Meanwhile, through the balance between global search and local search, they can effectively avoid falling into the low-quality local optimal solution (Alba and Dorronsoro, 2005). Consequently, meta-heuristic algorithms have become a popular and powerful way to engineer optimization problems.

So far, most meta-heuristic algorithms have been designed from different nature phenomena (Askari et al., 2020), e.g., animal hunting and human learning. Among all of these meta-heuristic algorithms, there is no one able to tackle every optimizing issue with a good performance based on the No-Free-Lunch theorem (Wolpert and Macready, 1997). In fact, each meta-heuristic algorithm can show superior performance in only some kinds of optimization problems compared with most of the other algorithms (Zhao et al., 2019). This is also the main reason why so many different meta-heuristic algorithms have been designed and proposed.

According to the number of searching individuals, the meta-heuristic algorithms can be divided into two categories, including the single-individual-based and population-based algorithms (Mirjalili et al., 2014). It is noticeable that the single-individual-based algorithms with simple searching operations require fewer fitness evaluations and computation time than those of the second category (Mas et al., 2009). However, it is also easily trapped in a low-quality local optimum since the single individual is difficult to increase the solution diversity while guaranteeing an efficient search, such as simulated annealing (SA) (Kirkpatrick et al., 1983) and tabu search (TS) (Glover, 1989). In another aspect, population-based methods (Mirjalili et al., 2014) can effectively improve the optimization efficiency and global searching ability via a specific cooperation between different individuals. In contrast to the single-individual-based algorithms, the population-based algorithms need to consume more computation time to execute adequate fitness evaluations for exploration and exploitation.

The video robot system has the benefits of high strength, high precision, and good repeatability. Meanwhile, it has a strong ability to withstand extreme environments, so it can complete a variety of tasks excellently (Mas et al., 2009). Although the majority of video robots execute these tasks in an isolated mode, increasing attention is being paid to the use of closely interacting clustered robotic systems. The potential benefits of clustered robotic systems include redundancy, enhanced footprint and throughput, resilient irreconcilability, and diverse features in space. A key feature among these considerations is the technology utilized to coordinate the movement of individuals.

In this article, a new machine learning-based hybrid algorithm named like-attracts-like optimizer (LALO) is also proposed based on solution clustering. Video clustering robots require optimization algorithms for further planning of their routes during population coordination in order to achieve

higher efficiency. For this problem, the proposed LALO algorithm can perform the corresponding optimization. It essentially mimics the social behavior of human beings where an excellent person easily attracts like-minded people to approach them (Fritzke et al., 1995; Fišer et al., 2013). Similarly, all the searching individuals in LALO will be divided into multiple clusters by a growing neural gas (GNG) network (Mirjalili et al., 2014) according to their positions. Different from the conventional clustering methods, the topological relations between different clusters can be generated for guided optimization (See Figure 1).

The rest of this article is organized as follows: Section 2 provides the principle and the detailed operations of LALO. The discussions of optimization results in unimodal benchmark functions are given in Section 3. At last, Section 4 concludes this work.

2 Like-attracts-like optimizer

2.1 Inspiration

Like-attracts-like is one of the main parts of social interactions which shows an excellent person easily drives like-minded people to approach them; thus, a group of people with similar features will be formed, as illustrated in Figure 2 (Gutkin et al., 1976). Inspired by this social behavior, a searching individual can represent a person in like-attracts-like, while each cluster can be regarded as a group of people. In this work, the proposed LALO is mainly designed according to the interaction network of different clusters.

2.2 Optimization principle and mathematical model

LALO is mainly composed of two stages: the clustering stage and the searching stage. Particularly, the clustering stage is achieved by the GNG network, and the searching stage is designed by combining the encircling prey of gray wolf optimizer (GWO) depending on the interaction network of the different clusters.

2.2.1 Clustering phase by the GNG network

As a form of unsupervised learning, the GNC network (Fišer et al., 2013) can dynamically adjust its topological structure to match the input data without any desired outputs. It can not only achieve fast data clustering but also keep a topological structure to guide the optimization. In general, the GNC network contains a set of nodes V and a set of edges E without weights, i.e., $G = (E, V)$, in which each node represents a cluster; $V = \{v_1, v_2, \dots, v_n\}$; and $E \subseteq V \times V$. The nodes and the edges will be dynamically changed to adapt to the input data (i.e., the solutions at the current iteration). Overall, the



FIGURE 1
Video robotics in real-world grid applications.

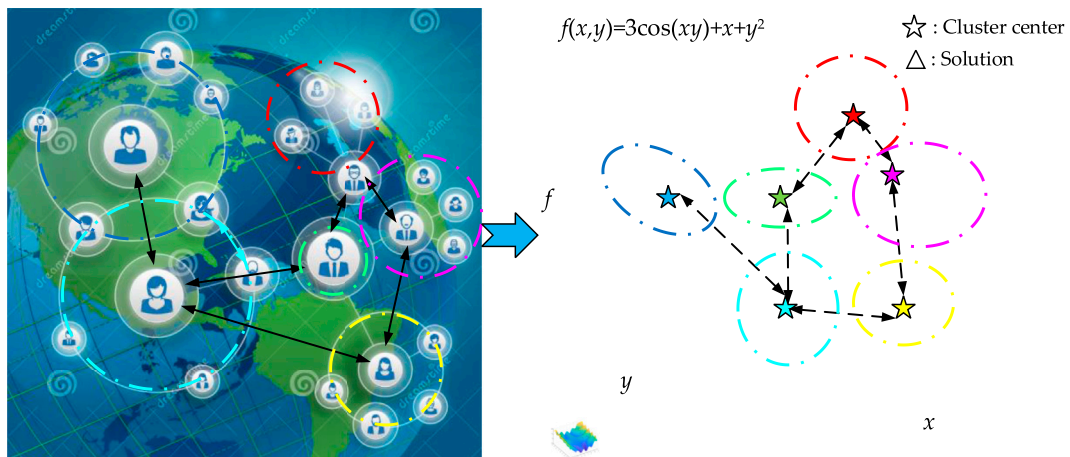


FIGURE 2
Illustration of like-attracts-like and its connection with optimization.

GNG network-based clustering phase contains ten steps as follows (Fritzke et al., 1995):

Step 1. Initialize the network from two nodes, in which the positions of these two nodes are randomly generated within the lower and upper bounds of the input data, as

$$\omega_1 \text{ or } \omega_2 = x_{lb}(k) + \vec{r}_0 * [x_{ub}(k) - x_{lb}(k)], \quad (1)$$

$$\begin{cases} x_{lb}^d(k) = \min_{i=1,2,\dots,N} x_i^d(k), & d = 1, 2, \dots, D, \\ x_{ub}^d(k) = \max_{i=1,2,\dots,N} x_i^d(k), & d = 1, 2, \dots, D, \end{cases} \quad (2)$$

where $x_{lb}(k)$ and $x_{ub}(k)$ are the vectors of the lower and upper bounds of the input data, respectively, with $x_{lb}(k) = \{x_{lb}^1(k), x_{lb}^2(k), \dots, x_{lb}^d(k), \dots, x_{lb}^D(k)\}$ and

$\vec{x}_{ub}(k) = \{x_{ub}^1(k), x_{ub}^2(k), \dots, x_{ub}^d(k), \dots, x_{ub}^D(k)\}$; $x_i^d(k)$ represents the position of the d th dimension of the i th individual in LALO; $\vec{r}_0$ is a random vector within the range from 0 to 1; k denotes the k th iteration of LALO; N is the population size of LALO; d denotes the d th dimension of the solution, and D is the number of dimensions.

Step 2. Randomly select a solution ξ from the input data and determine the nearest and the second nearest nodes according to their distances as

$$\begin{cases} n_1 = \arg \min_{c \in V} \|\omega_c - \xi\|^2, \\ n_2 = \arg \min_{c \in V, c \neq n_1} \|\omega_c - \xi\|^2, \end{cases} \quad (3)$$

where n_1 and n_2 represent the numbers of the nearest and the second nearest nodes, respectively; and ω_c is the position of the c th node.

Step 3. Update the age of all the edge links with the nearest node as

$$\text{Age}(n_1, j) = \text{Age}(n_1, j) + 1, \forall (n_1, j) \in E, \quad (4)$$

where $\text{Age}(n_1, j)$ denotes the age of the edge (n_1, j) .

Step 4. Update the accumulated error of the nearest node as

$$\text{Error}(n_1) = \text{Error}(n_1) + \|\omega_{n_1} - \xi\|^2, \quad (5)$$

where $\text{Error}(n_1)$ denotes the accumulated error of the node n_1 .

Step 5. Update the positions of the nearest node and its linked nodes as

$$\begin{cases} \omega_{n_1} = \omega_{n_1} + \varepsilon_1 (\xi - \omega_{n_1}), \\ \omega_j = \omega_j + \varepsilon_2 (\xi - \omega_j), \forall (n_1, j) \in E, \end{cases} \quad (6)$$

where ε_1 and ε_2 represent the learning rates of the nearest node and its linked nodes, respectively.

Step 6. If $(n_1, n_2) \in E$, then $\text{Age}(n_1, n_2) = 0$; otherwise, create the edge (n_1, n_2) in the network.

Step 7. If $\text{Age}(i, j) > t_{\max}$, then remove the edge (i, j) from the network, where $t_{\max}$ is the maximum allowable age of each edge. If a node does not have any adjacent nodes, then remove this node from the network.

Step 8. Insert a new node if the time of network learning is an integral multiple of the inserting rate λ , i.e., $\text{Time} \equiv 0 \pmod{\lambda}$. Particularly, the new node r should be inserted halfway between the node p with the largest accumulated error and its adjacent node q with the largest accumulated error, as

$$\begin{cases} p = \arg \max_{i \in V} \text{Error}(i), \\ q = \arg \max_{j \in \Omega_i} \text{Error}(j), \end{cases} \quad (7)$$

$$\omega_r = 0.5 \times (\omega_p + \omega_q), \quad (8)$$

where Ω_i is the set of the neighborhood of node i .

Along with the new node r , the original edge (p, q) should be removed, while the new edges (p, r) and (r, q) should be added. At the same time, the accumulated errors of these three nodes are updated as

$$\begin{cases} \text{Error}(r) = \text{Error}(p) = \alpha \cdot \text{Error}(p), \\ \text{Error}(q) = \alpha \cdot \text{Error}(q), \end{cases} \quad (9)$$

where α is the error decreasing factor for the new node and its neighborhood.

Step 9. Decrease the accumulated errors of all the nodes, as

$$\text{Error}(j) = \beta \cdot \text{Error}(j), \quad j \in V, \quad (10)$$

where β is the error-decreasing factor for all the nodes.

Step 10. Export the network if the conditions for termination are fulfilled; otherwise, switch to Step 2.

2.2.2 Searching phase

In LALO, each individual will approximate a better individual (i.e., the learning target) with a high-quality solution; thus, a potentially better solution can be found with a higher probability. This process is achieved based on the encircling prey of gray wolf optimizer (GWO) (Mirjalili et al., 2014). To guarantee high solution diversity (Gutkin et al., 1976), the learning target (See Figure 3) is selected from the interactive clusters or the best solution so far, according to solution comparison between adjacent clusters as follows:

$$x_j^{\text{best}}(k) = \arg \min_{x_i(k) \in X_j, i=1,2,\dots,N} \text{Fit}(x_i(k)), \quad (11)$$

$$x_j^{\text{target}}(k) = \arg \min_{m=j,m \in \Omega_j} \text{Fit}(x_m^{\text{best}}(k)), \quad (12)$$

$$x_i^{\text{target}}(k) = \begin{cases} x_j^{\text{target}}(k), & \text{if } x_i(k) \in X_j \text{ and } \text{Fit}(x_j^{\text{best}}(k)) < \text{Fit}(x_i^{\text{target}}(k)), \\ x_{sf}^{\text{best}}(k), & \text{if } \text{Fit}(x_j^{\text{best}}(k)) \geq \text{Fit}(x_i^{\text{target}}(k)), \end{cases} \quad (13)$$

where $x_j^{\text{best}}(k)$ is the best solution in the j th cluster; $x_j^{\text{target}}(k)$ is the best solution in the social network of the j th cluster; $x_i^{\text{target}}(k)$ is the learning target of the i th individual; $x_{sf}^{\text{best}}(k)$ is the best solution so far by LALO; X_j is the solution set of all the individuals in the j th cluster; and Fit denotes the fitness function for a minimum optimization.

Based on the selected learning target, the position of each individual can be updated as follows (Zeng et al., 2017):

$$x_i(k+1) = x_i^{\text{target}}(k) - \vec{A} \cdot \vec{L}, \quad (14)$$

$$\vec{A} = 2a \cdot \vec{r}_1 - a, \quad (15)$$

$$\vec{L} = |2\vec{r}_2 \cdot x_i^{\text{target}}(k) - x_i(k)|, \quad (16)$$

where $\vec{A}$ is the coefficient vector to approach the learning target; $\vec{L}$ is the difference vector between the individual and its learning target; $\vec{r}_1$ and $\vec{r}_2$ are the random vectors ranging from 0 to 1; and a is a coefficient.

2.2.3 Dynamic balance between exploration and exploitation

Like many meta-heuristic algorithms, LALO also requires wide exploration in the early phase (Heidari et al., 2019). As the iteration number increases, the exploration weight should be gradually weakened, while the exploitation weight should be gradually enhanced. To achieve a dynamic balance between them, the cluster number n and the coefficient a are decreased as the iteration numbers increase as follows:

$$n = \text{round}\left(n_{\max} - (n_{\max} - n_{\min}) \cdot \frac{k}{k_{\max}}\right), \quad (17)$$

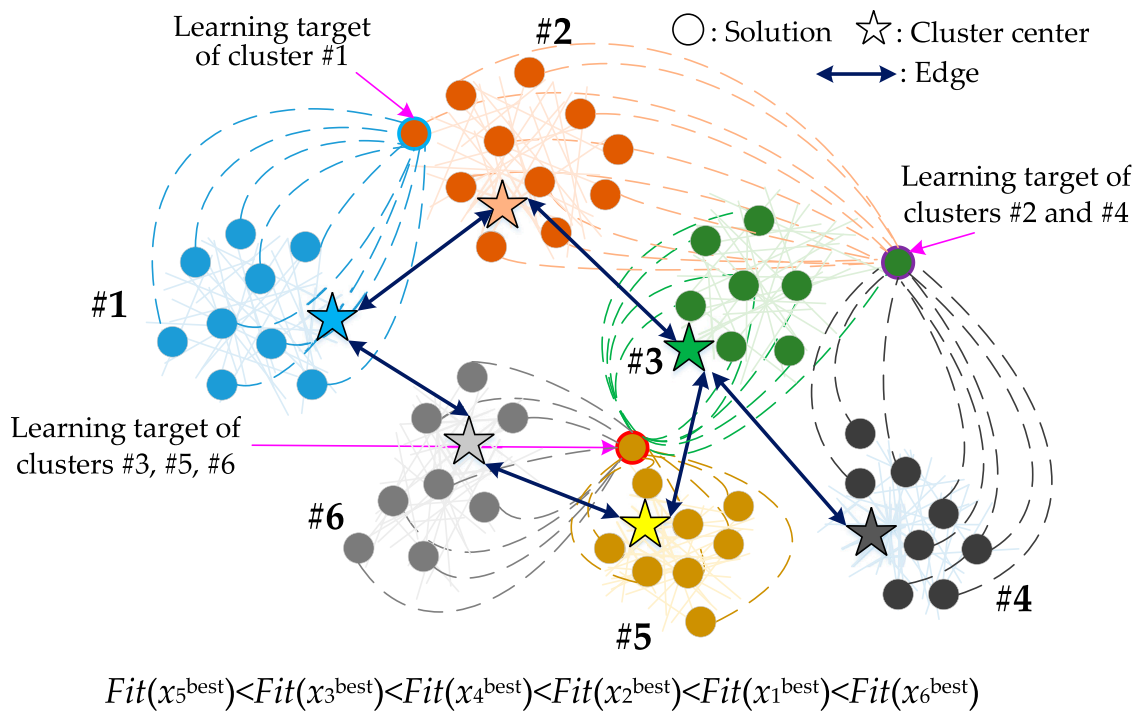


FIGURE 3

Illustration of the learning target-based searching phase of multiple interactive clusters in LALO.

$$a = 2 \cdot \left(1 - \frac{k}{k_{\max}}\right), \quad (18)$$

where $n_{\max}$ and $n_{\min}$ are the maximum and minimum number of clusters, respectively; and $k_{\max}$ is the maximum iteration number of LALO.

2.2.4 Pseudocode of LALO

To summarize, the pseudocode for LALO is provided in algorithm 1, where T is the iteration number in the GNC network and $T_{\max}$ is the corresponding maximum iteration number (i.e., the termination condition of the GNC network).

Algorithm 1 Pseudocode of LALO

```

1: Initialize the algorithm parameters;
2: Randomly initialize the population within the lower and upper bounds of optimization variables;
3: Calculate the fitness of each individual;
4: Set  $k:=1$ ;
5: While  $k \leq k_{\max}$ 
6:   Initialize the GNC network with two nodes by Eqs. (1)-(2); Clustering phase
7:   For  $T:=1$  to  $T_{\max}$ 
8:     Update the GNC network with the current population by Eqs. (3)-(10);
9:   End For
10:  Determine the clusters for the current population according to the obtained GNC network;
11:  For  $i:=1$  to  $n$ 
12:    Determine the learning target for the  $i$ th individual by Eqs. (11)-(13);
13:    Update the position of the  $i$ th individual by Eqs. (14)-(16); Searching phase
14:  End For
15:  Update the cluster number  $n$  and the coefficient  $a$ ;
16:  Set  $k:=k+1$ ;
17: End While
18: Output the optimal solution  $x_{sf}^{best}$ .

```

TABLE 1 Main parameters of LALO.

ε_1	ε_2	$t_{\max}$	λ	α	β	$n_{\max}$	$n_{\min}$	$T_{\max}$
0.5	0.005	5	5	0.1	0.9	12	4	150

TABLE 2 Unimodal benchmark functions.

Function	D	Range	$f_{\min}$
$F_1(x) = \sum_{i=1}^n x_i^2$	30	$[-100, 100]$	0
$F_2(x) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $	30	$[-10, 10]$	0
$F_3(x) = \sum_{i=1}^n (\sum_{j=1}^i x_j)^2$	30	$[-100, 100]$	0
$F_4(x) = \max_i \{ x_i , 1 \leq i \leq n\}$	30	$[-100, 100]$	0
$F_5(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$	30	$[-30, 30]$	0
$F_6(x) = \sum_{i=1}^{n-1} (x_i + 0.5)^2$	30	$[-100, 100]$	0
$F_7(x) = \sum_{i=1}^n ix_i^4 + \text{random}[0, 1)$	30	$[-1.28, 1.28]$	0

3 Like-attracts-like optimizer for unimodal benchmark functions

In this section, unimodal features are adopted to test the capability of LALO. Meanwhile, nine well-known meta-heuristic algorithms, namely, GWO (Mirjalili et al.,

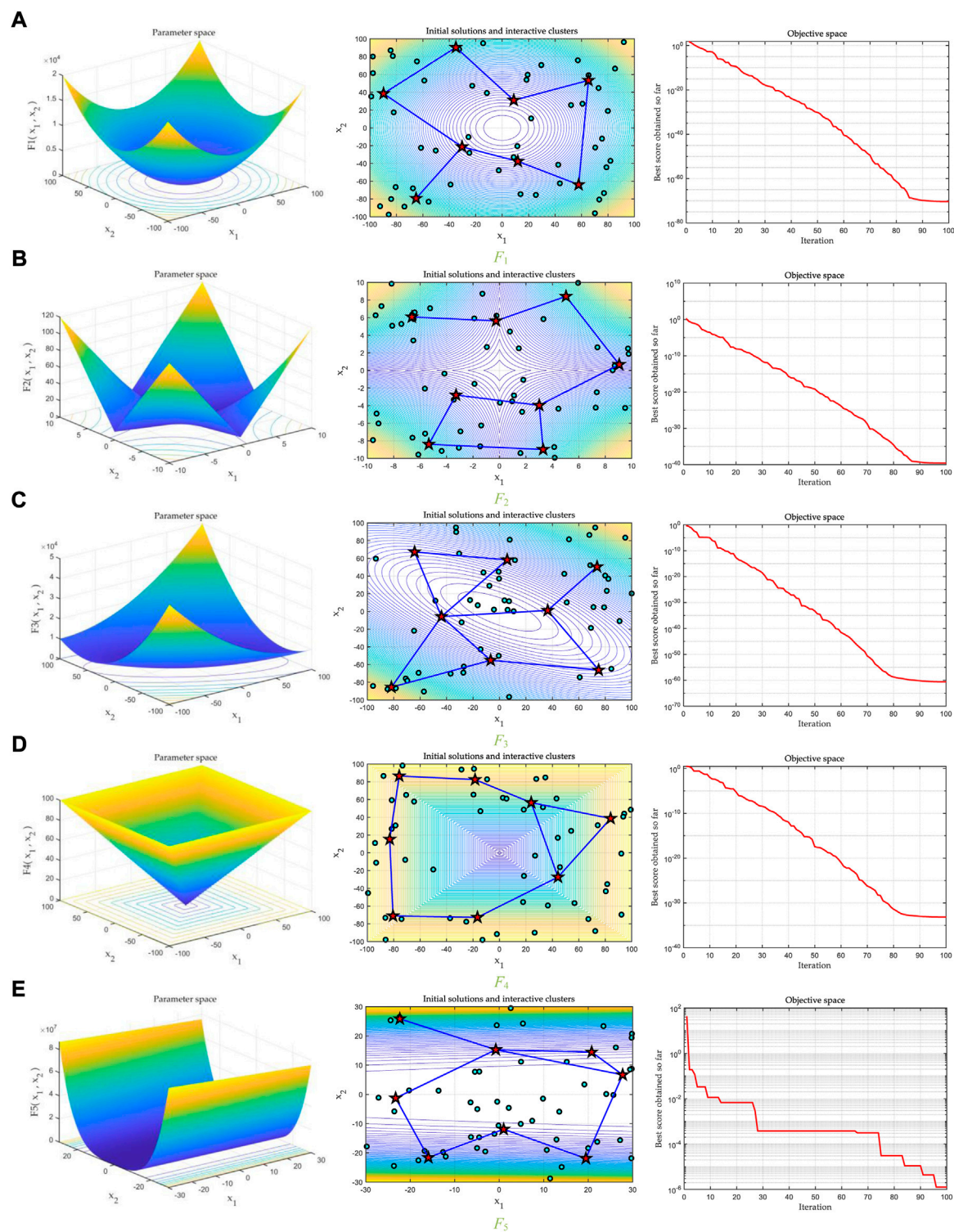


FIGURE 4
(Continued).

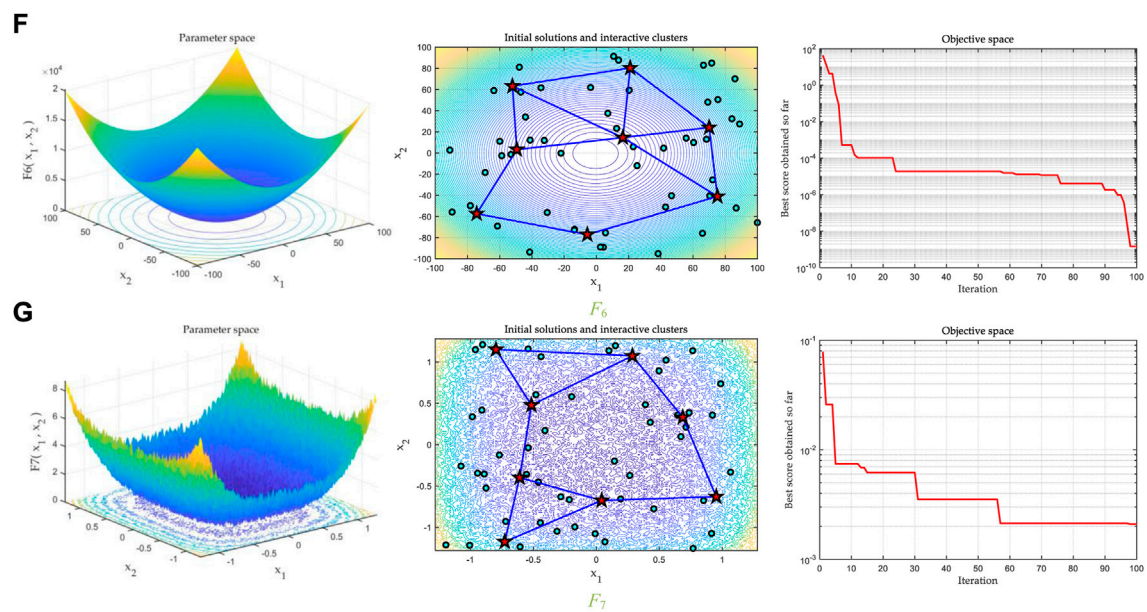


FIGURE 4

(Continued).

LALO for unimodal benchmark functions ($D = 2$) with searching space, initial solutions, interactive clusters, and the fitness curve. (A) F_1 ; (B) F_2 ; (C) F_3 ; (D) F_4 ; (E) F_5 ; (F) F_6 .

TABLE 3 Average fitness and rank obtained by different algorithms for unimodal benchmark functions in 30 runs.

Function	Metrics	LALO	EO	PSO	GWO	GA	GSA	SSA	CMA-ES	SHADE	LSHADE-SPACMA
F_1	Avg.	1.31E-37	3.32E-40	9.59E-06	6.59E-28	0.55492	2.53E-16	1.58E-07	1.42E-18	1.42E-09	0.2237
	Rank	2	1	8	3	10	5	7	4	6	9
F_2	Avg.	4.09E-27	7.12E-23	0.02560	7.18E-17	0.00566	0.05565	2.66293	2.98E-07	0.0087	21.1133
	Rank	1	2	7	3	5	8	9	4	6	10
F_3	Avg.	1.84E-05	8.06E-09	82.2687	3.29E-06	846.344	896.534	1709.94	1.59E-05	15.4352	88.7746
	Rank	4	1	6	2	8	9	10	3	5	7
F_4	Avg.	7.27E-05	5.39E-10	4.26128	5.61E-07	4.55538	7.35487	11.6741	2.01E-06	0.9796	2.1170
	Rank	4	1	7	2	8	9	10	3	5	6
F_5	Avg.	26.02845	25.32331	92.4310	26.81258	268.248	67.5430	296.125	36.7946	24.4743	28.8255
	Rank	3	2	8	4	9	7	10	6	1	5
F_6	Avg.	0.137603	8.29E-06	8.89E-06	0.816579	0.5625	2.50E-16	1.80E-07	6.83E-19	5.31E-10	0.2489
	Rank	7	5	6	10	9	2	4	1	3	8
F_7	Avg.	0.002606	0.001171	0.02724	0.002213	0.04293	0.08944	0.1757	0.0275	0.0235	0.0047
	Rank	3	1	6	2	8	9	10	7	5	4
Average rank		3.43	1.86	6.86	3.71	8.14	7.00	8.57	4.00	4.43	7.00

EO: Equilibrium optimizer; PSO: Particle Swarm Optimization; GWO: Grey wolf optimizer; GA: Genetic algorithm; GSA: Gravitational search algorithm; SSA: Salp swarm algorithm; CMA-ES: Evolution strategy with covariance matrix adaptation; SHADE: Success-History based Adaptive Differential Evolution; LSHADE-SPACMA: SHADE with linear population size reduction hybridized with semi-parameter adaption of CMA-ES.

2014), GA (Holland, 1992), EO (Faramarzi et al., 2020), PSO (Kennedy and Eberhart, 1007), gravitational search algorithm (SSA) (Mirjalili et al., 2017), GSA (Rashedi et al., 2009), evolution strategy with covariance matrix adaptation (CMA-ES) (Hansen et al., 2003), success-history-based

parameter adaptation differential evolution (SHADE) (Tanabe and Fukunaga, 2013), and SHADE with linear population size reduction hybridized with the semi-parameter adaption of CMA-ES (LSHADE-SPACMA) (Faramarzi et al., 2020), are used for performance

TABLE 4 Fitness standard deviation and ranks obtained by different algorithms for unimodal benchmark functions in 30 runs.

Function	Metrics	LALO	EO	PSO	GWO	GA	GSA	SSA	CMA-ES	SHADE	LSHADE-SPACMA
F_1	Avg.	2.06E-37	6.78E-40	3.35E-05	1.58E-28	1.2301	9.67E-17	1.71E-07	3.13E-18	3.09E-09	0.148
	Rank	2	1	8	3	10	5	7	4	6	9
F_2	Avg.	4.70E-27	6.36E-23	0.04595	7.28E-17	0.01443	0.19404	1.66802	1.7889	0.0213	9.5781
	Rank	1	2	6	3	4	7	8	9	5	10
F_3	Avg.	2.35E-05	1.60E-08	97.2105	1.61E-05	161.499	318.955	11242.3	2.21E-05	9.9489	47.23
	Rank	4	1	7	2	8	9	10	3	5	6
F_4	Avg.	7.50E-05	1.38E-09	0.6773	1.04E-06	0.59153	1.74145	4.1792	1.25E-06	0.7995	0.4928
	Rank	4	1	7	2	6	9	10	3	8	5
F_5	Avg.	0.187512	0.169578	74.4794	0.793246	337.693	62.2253	508.863	33.4614	11.208	0.8242
	Rank	2	1	8	3	9	7	10	6	5	4
F_6	Avg.	0.118325	5.02E-06	9.91E-06	0.482126	1.71977	1.74E-16	3.00E-07	6.71E-19	6.35E-10	0.1131
	Rank	8	5	6	9	10	2	4	1	3	7
F_7	Avg.	0.000805	0.000654	0.00804	0.001996	0.00594	0.04339	0.0629	0.0079	0.0088	0.0019
	Rank	2	1	7	4	5	9	10	6	8	3
Average rank		3.29	1.71	7.00	3.71	7.43	6.86	8.43	4.57	5.71	6.29

EO: Equilibrium optimizer; PSO: Particle Swarm Optimization; GWO: Grey wolf optimizer; GA: Genetic algorithm; GSA: Gravitational search algorithm; SSA: Salp swarm algorithm; CMA-ES: Evolution strategy with covariance matrix adaptation; SHADE: Success-History based Adaptive Differential Evolution; LSHADE-SPACMA: SHADE with linear population size reduction hybridized with semi-parameter adaption of CMA-ES.

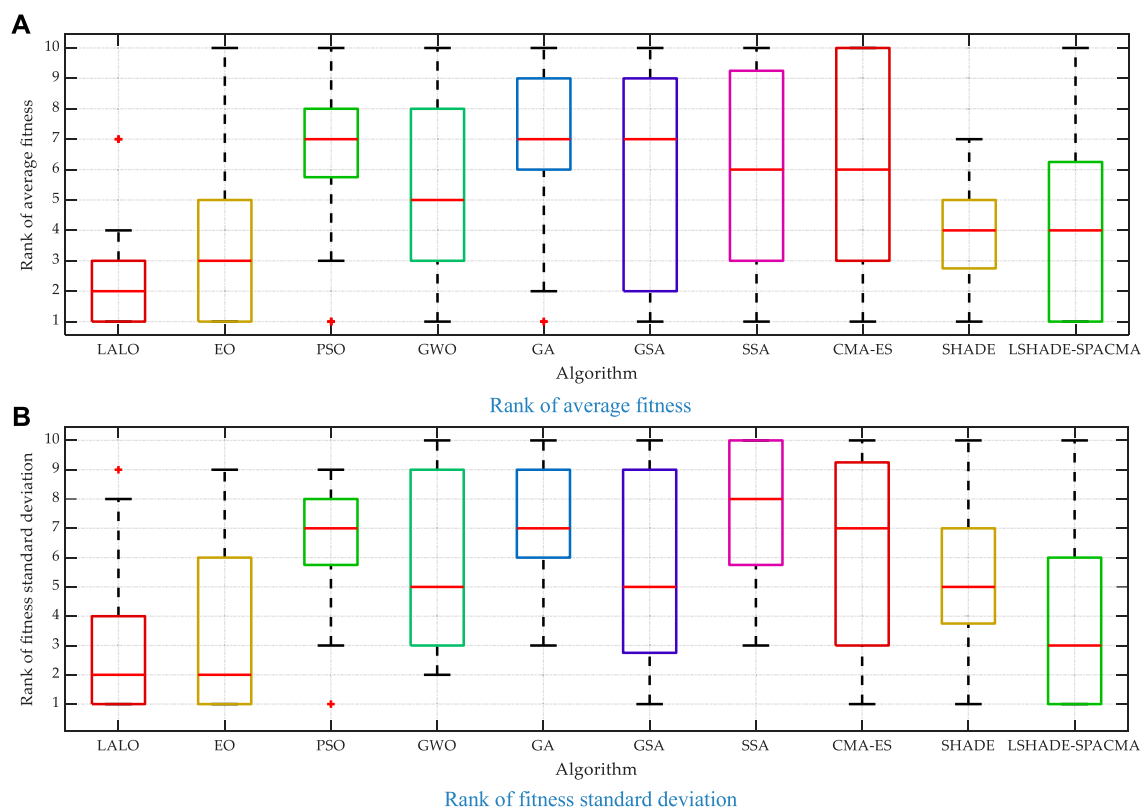


FIGURE 5

Box-and-whisker plots of ranks obtained by different algorithms for the benchmark functions from F_1 to F_7 . (A) Rank of average fitness. (B) Rank of fitness standard deviation.

comparisons, in which their parameters can be referred in Gutkin et al., 1976. To allow for an equitable competition, the maximum suitability rating for each algorithm was set to 15,000. Consequently, the population size and maximum iteration number of LALO are set to be 20 and 750, respectively, while other parameters can be determined *via* trial and error, as shown in Table 1. To clearly illustrate the searching process for the 2-dimensional benchmark functions, the population size and maximum iteration number of LALO are set to be 50 and 100, respectively; the maximum cluster number is set to be 8.

The unimodal benchmark functions F_1 to F_7 are given in Table 2, where range denotes the searching space of each optimization variable and f_{min} denotes the global optimum. Since each of them has only one global optimum, they are suitable to evaluate the exploitation ability of each meta-heuristic algorithm.

Figure 4 provides the searching space of the two-dimensional unimodal benchmark functions and the searching process of LALO, where the initial solutions and interactive clusters of LALO are also given. In consequence, the initial interactive clusters are distributed dispersedly, which can achieve wide exploration in the initial phase of LALO. As the iteration number increases, LALO can gradually find a better solution with an enhanced exploitation weight (Storn and Price, 1997; Regis, 2014).

Table 3 shows the average fitness and rank obtained by different algorithms for unimodal benchmark functions in 30 runs. It can be seen that LALO can obtain high-quality optimums on the whole for the unimodal benchmark functions, especially for function F_2 with the first rank. Particularly, the average rank of average fitness LALO is the highest among all the algorithms except EO for the seven unimodal benchmark functions (Rao et al., 2011; Jin, 2011; El-Abd, 2017; Jin et al., 2019). This effectively verifies the highly competent exploitation ability of LALO against the other nine meta-heuristic algorithms.

On the other hand, Table 4 gives the fitness standard deviation and rank obtained by different algorithms for the unimodal benchmark functions in 30 runs. Similarly, the average rank of the fitness standard deviation obtained by EO outperforms the other algorithms for the unimodal benchmark functions, followed by LALO. It reveals the high optimization stability of LALO compared with other algorithms for the unimodal benchmark functions.

Figure 5 provides the box-and-whisker plots of ranks obtained by different algorithms for the benchmark functions from F_1 to F_7 . It can be found from Figure 5A that the ranks of the average fitness obtained by LALO are mainly distributed in the top three for all the benchmark functions, which is the highest among all the algorithms. In contrast, the ranks of average fitness obtained by GA are

mainly distributed from 6 to 9, which demonstrate that it easily traps into a low-quality optimum due to premature convergence. Similarly, LALO also performs best among all the algorithms on the ranks of fitness standard deviation, as shown in Figure 5B. This sufficiently indicates that LALO is highly competitive compared to the presented nine meta-heuristic algorithms for the benchmark functions.

4 Conclusion

This article proposes a novel machine learning-based meta-heuristic algorithm, in which the main contributions can be summarized as follows:

- 1) The proposed LALO is a novel meta-heuristic algorithm inspired by the social behavior of human beings that states an excellent person easily attracts like-minded people to approach him or her. Compared with the traditional clustering-based meta-heuristic algorithm, LALO can not only divide the searching individuals into multiple clusters by using the GNG network but can also generate the interaction topology between different clusters. Hence, each individual can select its learning target from the interactive clusters; thus, a wide exploration can be implemented in the searching phase.
- 2) The exploration and exploitation of LALO can be dynamically balanced *via* adjusting the number of interactive clusters and the searching coefficient. As a result, it can enhance the exploration of LALO in the initial phase, while the exploitation can be gradually strengthened as the iteration number increases.
- 3) The comprehensive case studies are carried out to evaluate the optimization performance of LALO compared with various meta-heuristic algorithms. On the whole, LALO is highly competitive in the optimum quality and optimization stability for 29 benchmark functions and 3 classical engineering problems. Particularly, the simulation results clearly demonstrate that LALO is more appropriate to handle fix-dimension multimodal benchmark functions, composite benchmark functions, and classical engineering problems.

Due to the superior optimization performance of LALO, it can be applied to various real-world optimizations. Furthermore, it also can be extended into a multi-objective optimization algorithm to search the Pareto optimum solutions for different kinds of multi-objective optimization problems.

Data availability statement

The data analyzed in this study are subject to the following licenses/restrictions: Internal enterprise Data. Requests to access these datasets should be directed to Biao_Tang@outlook.com.

Author contributions

XH, BT, and MZ: writing the original draft and editing. YM and XM: discussion of the topic. LT, XW, and DZ: supervision and funding.

Funding

The authors gratefully acknowledge the support of the research and innovative application of key technologies of image processing and knowledge atlas for complex scenes in the Smart Grid (202202AD080004), the research and innovative applications of key technologies of image processing and knowledge atlas for complex scenes in the Smart Grid (YNKJXM20220019), the practical maintenance of substation inspection robot master station management

platform of Yunnan Electric Power Research Institute in 2022–2023 (056200MS62210005), and the Yunnan technological innovation talent training object project (No. 202205AD160005).

Conflict of interest

Authors XH, BT, MZ, YM, XM, and LT are employed by the Electric Power Research Institute of Yunnan Power Grid Co., Ltd., China Southern Power Grid. XW is employed by Yunnan Power Grid Co., Ltd., China Southern Power Grid. DZ is employed by Zhejiang Guozi Robotics Co., Ltd.

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OPEN ACCESS

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SPECIALTY SECTION
This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 17 August 2022
ACCEPTED 15 September 2022
PUBLISHED 10 January 2023

CITATION
Guilian W, Linyao Z, Tingting L, Hao C,
Wenlong L, Shaofang W, Jun Y and
Conghao L (2023), Forecast of total rural
energy demand based on energy
consumption intensity.
Front. Energy Res. 10:1021164.
doi: 10.3389/fenrg.2022.1021164

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Forecast of total rural energy demand based on energy consumption intensity

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It is necessary to build a simulation calculation model that is more in line with the actual rural energy endowment and development needs. Prediction and analysis of the total rural energy demand in the context of energy transition. The rural energy demand is affected by many factors, and the traditional single model contains very limited amount of information, which easily leads to a large deviation between the prediction results and the actual situation, thereby reducing the prediction accuracy. In view of this, in view of the complex and difficult to predict the influencing factors of rural energy demand under the new economic normal, based on the back propagation neural network-particle swarm-genetic hybrid optimization algorithm, a total rural energy demand forecast based on energy consumption intensity was constructed method. Firstly, select the key influencing factors of the total rural energy demand forecast and conduct path analysis to compare the explanation strength of the influencing factors on energy demand; secondly, construct the energy consumption demand regression model, and calculate the parameters based on the back propagation neural network-particle swarm-genetic hybrid optimization algorithm. Estimation results; finally, the scenario is given, and the regional rural energy demand forecast results are obtained by using the regression model. Empirical analysis shows that four aspects of GDP, industrial structure, energy utilization efficiency, and rural energy consumption are strongly correlated with the total rural energy demand. At the same time, the prediction error of this study can reach about 1.35%, which can predict future rural energy demand. The total amount to guide the construction of the rural energy system.

KEYWORDS

energy consumption intensity, energy demand forecast, particle swarm-genetic hybrid optimization algorithm, clean and low-carbon energy transformation, energy demand regression model

1 Introduction

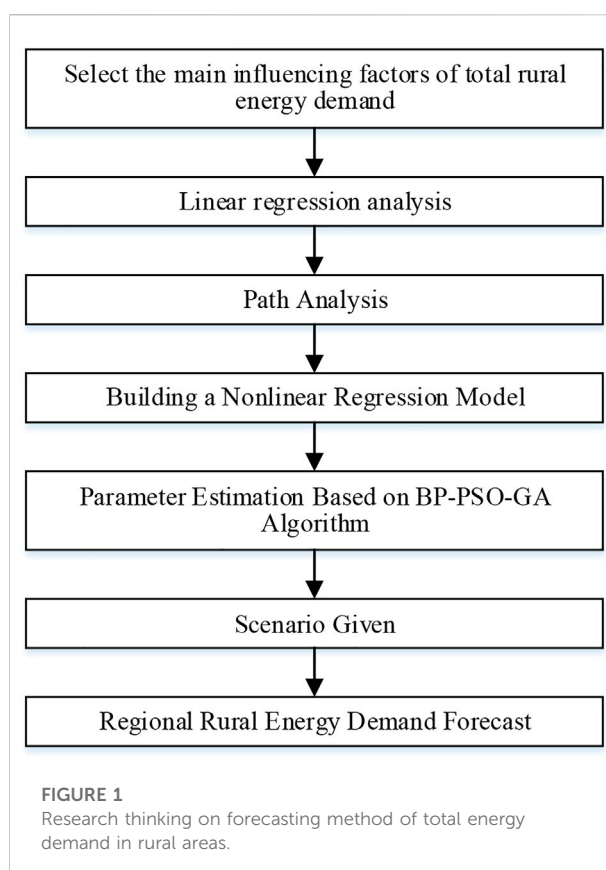
With the aggravation of environmental pollution and energy depletion, building a clean energy supply system has become a world trend (Xu et al., 2022), and rural areas will become the main battlefield for clean energy development with the advantages of abundant clean energy and sufficient space for clean energy development (Usman and Radulescu, 2022).

Under the rural revitalization, the development and system construction of clean energy in China's rural areas is of great significance to my country's sustainable development and the realization of environmental protection goals (Shi et al., 2021). It can effectively improve the rural energy consumption structure (Shao et al., 2022) and improve the backward production and living conditions, to promote energy conservation and emission reduction and social harmony (Li et al., 2021a).

For energy demand forecasting, traditional methods are mainly to build equations or models to fit the coupling relationship between economic development and energy consumption, so as to analyze the impact of economic development on energy demand (Li et al., 2021b), for example: through cointegration theory and Kuznets The curve is organically combined to analyze the complex relationship between energy consumption and economic development (Fan and Hao, 2020); the coupling relationship between energy consumption and economic growth is studied through co-integration analysis, and a VAR error correction model is constructed to improve the analysis accuracy (Wang et al., 2021); Correlation analysis model to determine the stable relationship between energy consumption and economic growth and has the characteristics of persistence (Ma and Li, 2020). Most of these studies focus on analyzing the causal relationship between economic growth and energy consumption to achieve energy demand forecasting. However, it is difficult to achieve high forecasting accuracy by only considering economic factors.

Energy demand forecasting is a complex nonlinear system. With the help of more accurate software analysis and the emergence of artificial intelligence models, emerging forecasting methods have gradually replaced traditional forecasting models. Benjamin F. Hobbs (Hobbs et al., 1998), Coskun Hamazaceb (2007) used the neural network model to predict the daily demand of domestic electricity, natural gas and other energy sources and the total energy consumption of Turkey, compared with traditional statistical analysis methods and models. On the basis of analyzing the influencing factors of energy consumption, Wang Jue and Bao Qin established a wavelet neural network model to predict China's energy consumption demand nonlinearly with high accuracy (Jnr et al., 2021). However, the above studies did not consider the correlation between the influencing factors in the selection of influencing factors, and under the complex influencing factors and trends, the total rural energy demand forecast is difficult to apply in practice.

Aiming at the problem that the influencing factors of rural energy demand are complex and difficult to predict under the new economic normal, this paper proposes a total rural energy demand forecast method based on energy consumption intensity. Firstly, select the key influencing factors of the total rural energy demand forecast and conduct path analysis to compare the explanatory power of the influencing factors to energy



demand. BP neural network-particle swarm-genetic hybrid optimization algorithm is used to calculate the parameter estimation results; finally, the future trends of the four aspects of GDP, industrial structure, energy utilization efficiency, and rural energy consumption proportion are given scenarios, and the regression model is used. Calculate the regional rural energy demand forecast results. This paper standardizes the calculation process, strengthens the key influencing factors, can more accurately predict the total energy demand in rural areas, and provides support for the construction of rural energy system.

2 Research ideas on forecasting method of total energy demand in rural areas

Figure 1 shows the research thinking of the total rural energy demand forecast method based on energy consumption intensity.

Step 1: Select the main influencing factors of the total rural energy demand and carry out regression analysis.

Step 2: According to the regression analysis results, select the key influencing factors of the total rural energy demand forecast and

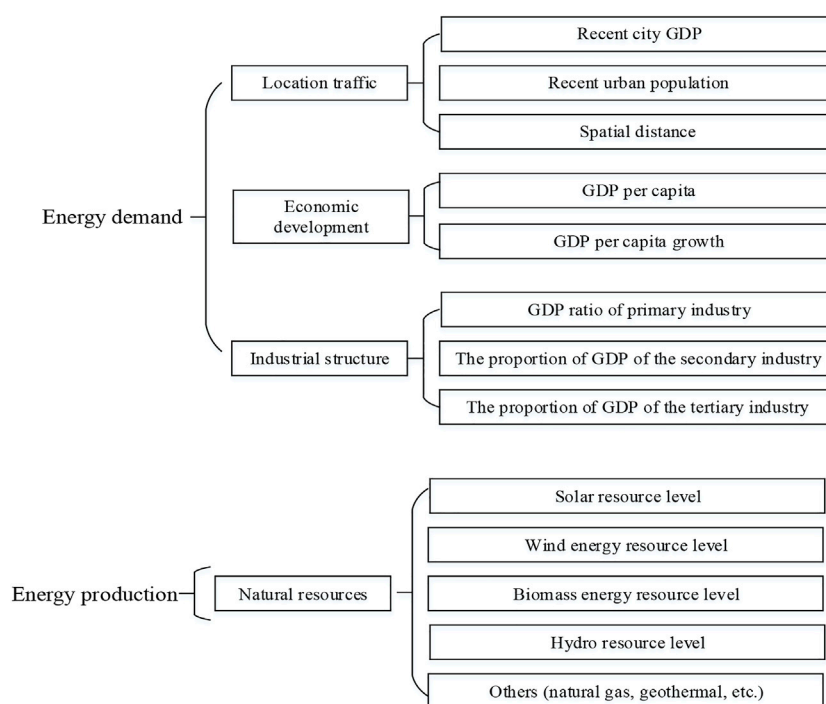


FIGURE 2

Classification index system of rural differentiated energy scenarios.

conduct path analysis, and compare the explanatory strength of the influencing factors to energy demand.

Step 3: Build a relational regression model between energy consumption demand and GDP, industrial structure, and energy utilization efficiency, and estimate parameters based on particle swarm-genetic hybrid optimization algorithm.

Step 4: Scenarios are given for the future trends of GDP, industrial structure, energy utilization efficiency, and the proportion of rural energy consumption, and the forecast results of regional rural energy demand are calculated using the parameter model in [Step 3](#).

3 Prediction method of total rural energy demand

3.1 Classification method of rural differentiated energy scenarios

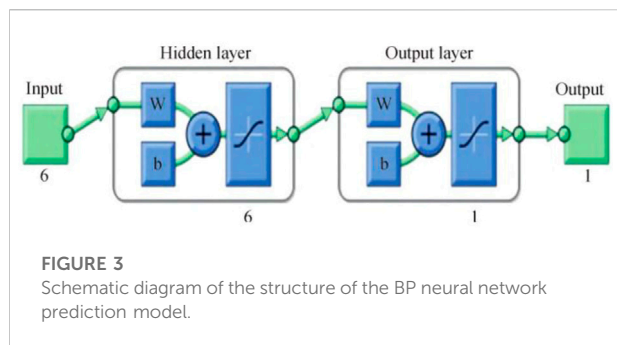
The influencing factors of energy demand include location and transportation, economic development, and industrial structure. Energy production includes natural resource endowment. An evaluation standard system is constructed to classify rural areas.

3.1.1 Location traffic as a classification criterion

Under the rural development goals, locational transportation represents the connection between the geographical location of the village itself and the city, which greatly affects the driving effect of regional development, which in turn affects the regional energy demand and growth rate. When the village is closer to the city and the transportation is more convenient, it will be more affected by urban radiation, which will affect its economic development and energy demand. The city's GDP and population size determine the strength of a city's influence, that is, the classification criteria for location traffic are traffic and urban radiation influence, and the judgment is based on the GDP, population, and the distance between the evaluation area center and the city.

3.1.2 Economic development as a taxonomy

The economy is the main internal driving force of rural development and is directly related to energy consumption demand. The county per capita GDP and per capita GDP growth rate reflect the development status and driving force of the rural economy. It is easier to obtain data than the income of different industries. It reflects whether there is an industry in the rural area, which can be developed into an industrial rural area. That is, the classification standard of economic development is village per capita GDP and per capita GDP growth rate.



3.1.3 Industrial structure as a classification criterion

There is a big difference in the energy consumption intensity of different industries. In the energy consumption intensity, the secondary industry > the tertiary industry > the primary industry. Therefore, the regional energy structure is also an important factor affecting energy demand. The secondary industry accounts for a high proportion and the energy demand is stronger. Therefore, the proportion of GDP of the primary industry, the proportion of GDP of the secondary industry, and the proportion of GDP of the tertiary industry are used as the influencing factors of rural energy demand forecast.

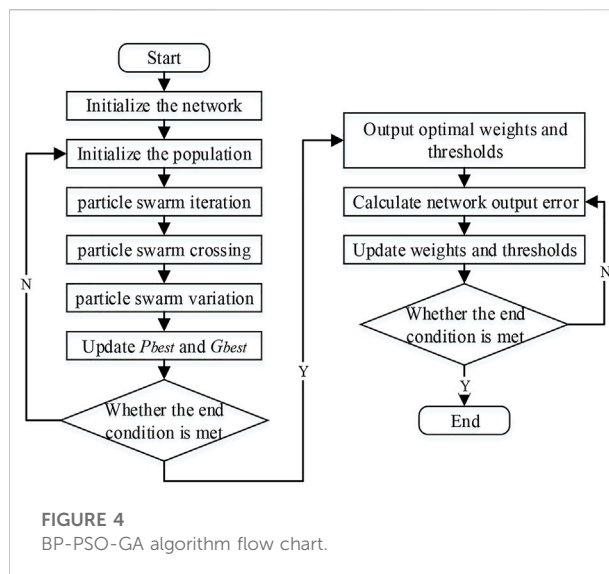
3.1.4 Resource endowment as a taxonomy

Resource endowment is an influencing factor that directly affects the construction of the energy system. As the new power system is dominated by the development of new energy sources such as wind power and photovoltaics, this study focuses on solar energy, wind energy, biomass energy, and water energy, geothermal and other energy sources are classified as other.

As shown in Figure 2, energy demand constructs influencing factor indicators from three aspects: location transportation, economic development, and industrial structure, and energy production constructs influencing factor indicators from resource endowment to form secondary classification influencing factors.

3.2 Introduction to path analysis methods

Path Analysis (Lu et al., 2019) is used to analyze the linear relationship between multiple independent variables and dependent variables. It can deal with more complex variable relationships and is mainly used to study the direct and indirect importance of independent variables to dependent variables. If $x_1, x_2, \dots, x_k$ are independent variables (influencing factors), y is the dependent variable (energy demand), and r_{ij} is the sample correlation coefficient between x_i and x_j , the normal equations of the path coefficients are as follows:



$$\begin{cases} p_{1y} + r_{12}p_{2y} + \dots + r_{1k}p_{ky} = r_{1y} \\ r_{21}p_{1y} + p_{2y} + \dots + r_{2k}p_{ky} = r_{2y} \\ \vdots \\ r_{k1}p_{1y} + r_{k2}p_{2y} + \dots + p_{ky} = r_{ky} \end{cases} \quad (1)$$

Among them, p_{iy} is the direct path part, that is, the partial correlation coefficient between x_i and y , indicating the direct effect of the independent variable x_i on y ; $r_{ij}p_{jy}$ is the indirect path, indicating the indirect effect of x_i on y through x_j ; $\sum_{i \neq j} r_{ij}p_{jy}$ represents the sum of the indirect effects of x_i on y . It can be seen from the equation that the correlation r_{iy} between the independent variable x_i and the dependent variable y can be divided into the direct path part p_{iy} and the indirect path part $\sum_{i \neq j} r_{ij}p_{jy}$. Because of the complexity of the energy economy, it is impossible for the model to include all the influencing factors. In addition to the influence of the variables already listed on the dependent variable, the calculation formula for the path coefficient of the remaining error is:

$$p_{ay} = \sqrt{1 - \sum_{i=1}^k p_{iy}r_{iy}} \quad (2)$$

3.3 BP neural network algorithm based on particle swarm optimization and genetic algorithm

In order to further improve the accuracy of the rural energy demand prediction model and avoid the disadvantage of the slow convergence speed of the Genetic Algorithm (GA) (Jiang et al., 2020), based on the BP-GA (Huang et al., 2022) model, a Particle Swarm optimization (PSO) with a fast convergence speed is introduced

TABLE 1 Basic data of statistical yearbook.

Year	TEC (10,000 tons of standard coal)	GDP (100 million yuan)	Energy consumption intensity (ton of standard coal/ 10,000 yuan)	Secondary industry (100 million yuan)	Tertiary industry (100 million yuan)	Industry (100 million yuan)	Heavy industry (100 million yuan)
1980	710	87.06	8.16	35.68	19.43	81.45	31.97
1981	729	105.62	6.90	39.75	26.57	87.76	32.24
1982	780	117.81	6.62	42.92	30.65	95.77	35.73
2018	13131.01	35804.04	0.37	17232.36	16191.86	57732.35	28230.01
2019	13718.31	42395.00	0.32	20581.74	19217.03	63172.56	31110.46
2020	13905.19	43903.89	0.32	20328.80	20842.78	63476.68	31859.06

(Peng and Xiang, 2020), composed a back propagation neural network-particle swarm-genetic (BP-PSO-GA) hybrid algorithm, which can overcome the limitations of a single algorithm and achieve complementary advantages. The BP-PSO-GA algorithm has a better ability to search for the optimal solution globally, and has great advantages in fitness, convergence speed and prediction accuracy, thereby improving the overall performance of the algorithm.

PSO is a global random search algorithm that searches for the optimal solution through a group of particles that continuously adjust their position X_i and velocity V_i in space (Zhang et al., 2018). In this process, each particle can find an optimal solution, this solution is called the individual extreme value, which is represented by P_{best} . Share P_{best} with other particles, and take the best P_{best} in the entire particle swarm as the global optimal solution, which is called the global extremum, and is represented by G_{best} . The individual particles in the particle swarm then adjust X_i and V_i according to P_{best} and G_{best} to obtain the global optimal solution (Li et al., 2018). Where the adjustment formulas of X_i and V_i are:

$$X_{i+1} = X_i + V_{i+1} \quad (3)$$

$$V_{i+1} = wV_i + c_1r_1(P_{best} - X_i) + c_2r_2(G_{best} - X_i) \quad (4)$$

Where X_i represents the rural energy demand, w represents the inertia weight factor, c_1 and c_2 represent the learning factor, taking the value [0, 2], r_1 and r_2 represent the random number, taking the value [0, 1].

The whole process of the PSO algorithm is: particle swarm initialization, particle fitness calculation, finding P_{best} , finding G_{best} , updating X_i and V_i of particles, and outputting the final global optimal solution.

The established BP-PSO-GA network flow steps are as follows:

- 1) First determine the BP network structure. In order to compare the prediction results with BP and GA-BP neural network models, the BP network structure selection of this

TABLE 2 Linear regression results.

Variable	Mean	Standard deviation	Expected symbol
GDP	9690.73	12363.30	+
EFF	2.03	2.20	+
STR2	0.44	0.06	–
STR3	0.37	0.06	–
STR	0.0020	0.07	+

prediction model is consistent with them, and is determined as 6-6-1 structure. That is, the 6 parameters of loudness, AI index, fluctuation, roughness, sharpness, and A sound pressure level are used as 6 nodes in the input layer, 6 nodes are selected in the hidden layer, and 1 node in the output layer is the sound quality prediction result as shown in the Figure 3.

- 2) Initialize the network and initialize the particle swarm, and determine the value of each parameter: the chromosome length is 49, the population size is 40, the maximum evolutionary generation is 200, the crossover probability is 0.8, the mutation probability is 0.07, the maximum inertia weight factor is 0.9, the minimum inertia weight The value factor is 0.4, the learning factor is 2.
- 3) By calculating the fitness function, search P_{best} and G_{best} , and update the X_i and V_i of the particle swarm according to the rules.
- 4) Carry out the crossover operation of the particle swarm.

Select the particle with better fitness value, according to the set probability, use the position crossover operator and speed crossover operator of Eqs 5, 6 to compare the speed and position of the i th particle and the speed and position of the j th particle. Crossover is performed, and the particles with better fitness are put back into the particle swarm for the next step.

TABLE 3 Path analysis results.

Independent variable	Correlation coefficient with TEC	Direct path factor	Indirect path factor					
			Total	By GDP	By EFF	By STR2	By STR3	By STR
GDP	0.9345	0.7875	0.3799	—	−0.0578	0.0156	0.5842	−0.1621
EFF	−0.6545	0.6079	0.6304	−0.1783	—	−0.1331	0.3797	0.5621
STR2	0.1944	0.9702	0.0588	0.0425	0.0045	—	0.0876	−0.0758
STR3	0.5865	0.6370	0.5942	0.3216	0.3426	−0.0662	—	−0.0038
STR	0.3765	0.7314	0.465	0.7685	−0.3622	−0.0769	0.1356	—

$$\begin{cases} X_i(k+1) = \alpha X_i(k) + (1-\alpha)X_j(k) \\ X_j(k+1) = \alpha X_j(k) + (1-\alpha)X_i(k) \end{cases} \quad (5)$$

$$\begin{cases} V_i(k+1) = \beta V_i(k) + (1-\beta)V_j(k) \\ V_j(k+1) = \beta V_j(k) + (1-\beta)V_i(k) \end{cases} \quad (6)$$

In the formula: α and β represent random numbers between $[0, 1]$.

5) Carry out the mutation operation of the particle swarm.

Select the particle with poor fitness value according to the set probability, and perform mutation operation on the position and speed of the particle according to the position mutation and velocity mutation operators of Eqs 7, 8 respectively, and place the mutated particle again. Back to the particle swarm.

$$\begin{cases} X_i(k+1) = \alpha X_i(k) + (X_i(k) - X_{\max}) \cdot f(g), r_1 \geq 0.5 \\ X_j(k+1) = \alpha X_j(k) + (X_{\min} - X_i(k)) \cdot f(g), r_1 < 0.5 \end{cases} \quad (7)$$

$$\begin{cases} V_i(k+1) = \alpha V_i(k) + (V_i(k) - V_{\max}) \cdot f(g), r_2 \geq 0.5 \\ V_j(k+1) = \alpha V_j(k) + (V_{\min} - V_i(k)) \cdot f(g), r_2 < 0.5 \end{cases} \quad (8)$$

In the formula: $f(g) = r_3(1 - e_i/e_{\max})$, e_i is the current number of iterations, $e_{\max}$ is the maximum number of iterations, and r_1 , r_2 and r_3 are all random numbers between $[0, 1]$.

6) Update P_{best} and G_{best} .

7) Determine whether the PSO-GA iterative operation satisfies the end condition, and output the optimal weight and threshold, otherwise return to continue to initialize the population.

8) BP neural network weight threshold update.

9) Determine whether the BP neural network training has reached the end condition, if not, return to re-adjust the weight threshold and carry out training; if it is satisfied, the training ends. The BP-PSO-GA algorithm flow is shown in Figure 4.

4 Establishment of rural energy demand forecasting model

The direct influencing factors of energy consumption demand include three aspects: GDP, industrial structure and energy utilization efficiency (Morikawa, 2012). Establish an energy demand forecast model:

$$\ln TEC = \alpha + \beta \ln GDP + \sum \gamma_i STR_i + \delta EFF + \varepsilon \quad (9)$$

Among them, α , β , γ_i , and δ are the influence coefficients, and ε is the residual error. The change in coal consumption for power generation (EFF) is used to represent the change in energy utilization efficiency; STR_i is a variable to measure the change in industrial structure. Select the proportion of the secondary industry (STR_2), the proportion of the tertiary industry (STR_3), the proportion of heavy industry in the industry (STR_h), the interaction term (STR) of the proportion of the secondary industry and the proportion of heavy industry in the industry as the variables reflecting changes in industrial structure. The STR calculation formula is as follows:

$$STR = \frac{(STR_2 \times STR_h)}{100} \quad (10)$$

The particles in the BP-PSO-GA algorithm continue to find the optimal solution in the iterative process according to the size of the fitness value. In this paper, the reciprocal of the mean square error (MSE) is used as the fitness value function:

$$f = \frac{1}{MSE} = \left(\frac{1}{N} \sum_{i=1}^N (\hat{y}(i) - y(i))^2 \right)^{-1} \quad (11)$$

Where $\hat{y}(i)$ is the estimated value of energy demand, $y(i)$ is the actual value of energy demand, and N is the number of samples.

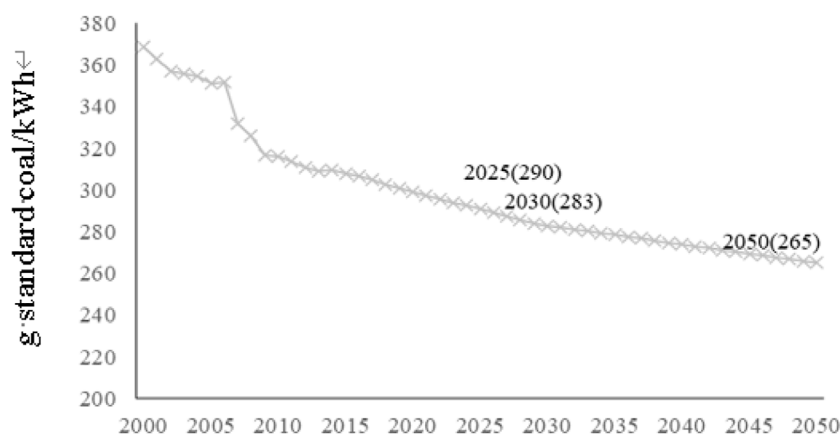


FIGURE 5
Energy efficiency given scenario.

5 Empirical analysis

5.1 Data selection

Based on historical data, judge the future trend of various influencing factors, and give the change scenarios of economic growth, industrial structure changes (the proportion of secondary industry, the proportion of tertiary industry, the proportion of heavy industry in industry), the improvement of energy utilization efficiency, and the proportion of rural energy consumption, and the relevant data value of the forecast year is obtained.

Based on the statistical yearbook data of a certain region, collect relevant data such as total energy demand, GDP, the proportion of secondary industry, the proportion of tertiary industry, and the proportion of heavy industry in industry from 1980 to 2020 in Table 1.

Due to the different measurement units and large differences in the quantity level of each variable. In order to ensure the accuracy and stability of the prediction, the data are standardized. The formula is as follows:

$$x' = (x_i - x_{\min}) / (x_{\max} - x_{\min}) \quad (12)$$

Where x' represents the processed data, and $x_{\max}$ and $x_{\min}$ represent the maximum and minimum values in the x_i data, respectively.

5.2 Path analysis

Generally, path analysis is meaningful when there is a significant correlation and regression relationship between the explained variable and the explanatory variable. Therefore,

taking TEC as the explained variable, GDP, energy consumption intensity (EFF), the proportion of the secondary industry ($STR2$), the proportion of the tertiary industry ($STR3$), the proportion of the secondary industry and the interaction term of the proportion of heavy industry in the industry (STR) as the explanatory variable for regression. The regression equation is as follows:

$$TEC = -0.4354 + 0.6576GDP + 0.7343EFF - 0.1233STR2 - 0.7545STR3 + 0.1744STRh \quad (13)$$

The linear regression results are shown in Table 2. The R^2 is 0.9937, the F statistic is 6168.73, and the overall fit of the model is good. Therefore, it is meaningful to do the path analysis of GDP , EFF , $STR2$, $STR3$ and STR in TEC . According to Eqs 1, 2, the direct path coefficient of the error is:

$$p_{ay} = \sqrt{1 - \sum_{i=1}^k p_{iy}r_{iy}} = \sqrt{1 - R^2} = 0.1121 \quad (14)$$

Through the formula, the direct path coefficient and indirect path coefficient of each variable and dependent variable can be calculated, as shown in Table 3. The path coefficient analysis shows that GDP , energy consumption intensity (EFF) and the proportion of the tertiary industry ($STR3$) have a greater impact on the total energy demand (TEC), and the correlation coefficients are 0.9345, 0.6545 and 0.5865, respectively. The proportion of the secondary industry ($STR2$) and the interaction term (STR) of the proportion of secondary industry and the proportion of heavy industry in the industry have relatively small effects on total energy demand (TEC), which are 0.1944 and 0.3765, respectively.

TABLE 4 Analysis of training sample prediction results.

Year	Actual value	PSO		GA		BP-PSO-GA	
		Predictive value	Error (%)	Predictive value	Error (%)	Predictive value	Error (%)
2016	12035.99	12280.32	2.03	11632.78	3.35	12205.00	1.15
2017	12554.74	12778.21	1.78	12946.45	3.12	12694.11	1.92
2018	13131.01	12832.94	2.27	13481.61	2.67	12965.27	1.26
2019	13718.31	13534.48	1.34	14339.75	4.53	13796.51	1.38
2020	13905.19	13558.95	2.49	14288.97	2.76	14114.02	1.06

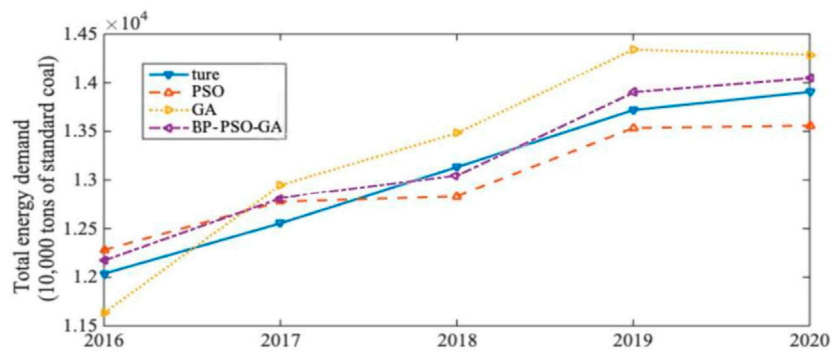


FIGURE 6

Comparison of training sample prediction results.

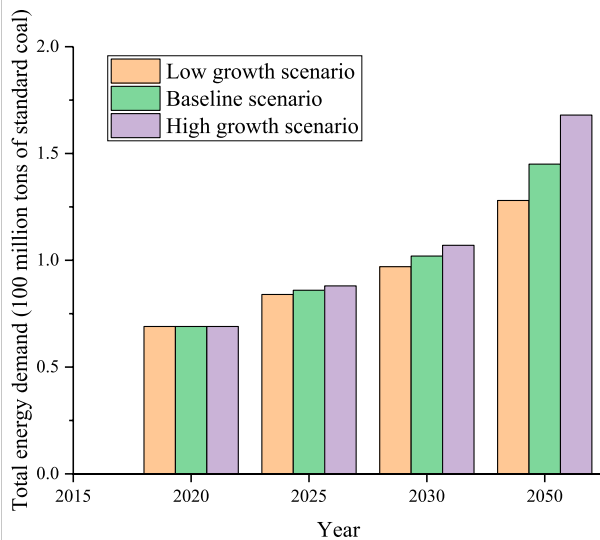


FIGURE 7

Prediction results of total regional rural energy demand.

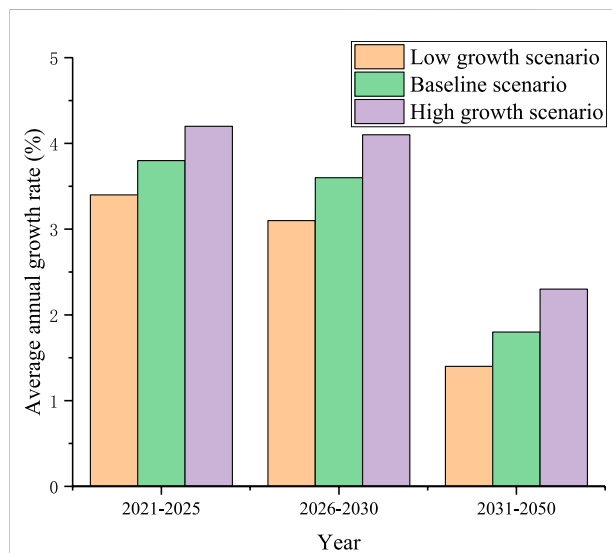


FIGURE 8

Forecast results of regional rural energy demand growth rate.

5.3 Scenario given

Scenarios are given for the economic growth rate, industrial structure, energy utilization efficiency, and the proportion of rural energy, and the forecast results of the total rural energy consumption are calculated.

5.3.1 Economic growth rate

There are three scenarios for future economic growth:

1) The first scenario is the low growth scenario. The economic growth rates for the three periods of 2021–2025, 2026–2030, and 2031–2050 are set to be 5.0%, 4.0%, and 2.5%, respectively.

2) The second scenario is the baseline scenario. The economic growth rates for the three periods of 2021–2025, 2026–2030, and 2031–2050 are set to be 5.5%, 4.5%, and 3.0%, respectively.

3) The third scenario is the high-growth scenario. The economic growth rates for the three periods of 2021–2025, 2026–2030, and 2031–2050 are set to be 6.0%, 5.0%, and 3.5%, respectively.

5.3.2 Industrial structure

In general, China's industrial process has entered the late stage. The continuous rise of the proportion of the tertiary industry and the continuous decline of the proportion of the primary and secondary industries are the characteristics of the industrial structure. It is assumed that the proportion of the tertiary industry will increase from 47.5% in 2020 to 54.7% in 2030, and then to 65.0% in 2050; the proportion of the secondary industry will decrease from 46.3% in 2020 to 37.6% in 2030, and then to 30.5% in 2050; the proportion of primary industry will drop from 6.2% in 2020 to 5.5% in 2030, and then to 4.5% in 2050; the proportion of the total output value of the regional heavy industry in the total industrial output value will remain at around 50% by 2030, and will gradually decrease to 45% by 2050.

5.3.3 Energy utilization efficiency

In the past, the space for energy resources and ecological environment was relatively large. Now the environmental bearing capacity has reached or approached the upper limit. The green and low-carbon cycle development of the economy has become a new requirement, and the cost of energy use will further increase. This has more incentives for the improvement of energy efficiency. In this paper, the coal consumption of power generation is used to represent the energy utilization efficiency, and the autoregressive value of this time series is used as a given scenario to represent the future trend of energy utilization efficiency improvement, as shown in Figure 5.

5.3.4 Proportion of rural energy consumption

In 2020, regional rural energy consumption accounts for 50% of the total. With the accelerated development of rural urbanization and the gradual expansion of the tide of returning home from cities, the development of modern rural industries will change with each passing day. It is estimated that by 2025, the proportion of rural energy consumption will reach 53% of the province's total energy consumption, 57% by 2030, and 65% by 2050, and the urban-rural equalization will reach a sustainable level.

5.4 Total rural energy consumption forecast

The algorithm was written and tested in MATLAB R2014a, and the standardized data of influencing factors and total energy consumption from 1980 to 2015 were used as model input. Combined with the previous research and trial and error results, the parameters of the model are set as: particle swarm size $pop_size = 200$, maximum number of iterations $max_gen = 500$, $max_k = 50$, $M = 50$, learning factor $C_1 = C_2 = 2.1$, inertia weight $x = 2/|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}|$, where $\varphi = C_1 + C_2$, mutation probability $P_m = 0.1$, hybridization probability $P_c = 0.8$, upper limit of independent variable $a = -10$, lower limit $b = 10$. After testing, the results of the energy demand model are as follows:

$$TEC = -0.4354 + 0.6576GDP + 0.7343EFF - 0.1233STR2 - 0.7545STR3 + 0.1744STRh \quad (15)$$

In the fitting stage, the mean absolute error (MAE) of the model is 1.3503%, which is ideal. In order to further test the effectiveness of the improved model, the data from 2016 to 2020 was used as the test sample for prediction and estimation, and the predicted values predicted by the PSO algorithm, the GA algorithm and the BP-PSO-GA algorithm were compared with the actual values, as shown in Table 4; Figure 6.

From the prediction results, it can be found that the average absolute error of prediction using the PSO algorithm is 1.98%, the average absolute error of using the GA algorithm is 3.29%, and the average absolute error of using the BP-PSO-GA algorithm is 1.35%. It can be seen that the improved BP-PSO-GA algorithm has higher prediction accuracy.

Based on the scenarios given in the previous section, the predicted results of regional rural energy demand are shown in Figures 7, 8.

6 Conclusion

This paper proposes a forecasting method of total rural energy demand based on energy consumption intensity. First, select the key influencing factors of the total rural energy demand forecast and conduct path analysis to compare the explanatory power of the influencing factors to energy demand; Then, the parameter estimation results are calculated based on the BP-PSO-GA algorithm; finally, the scenario is given, and the regional rural energy demand forecast results are calculated by using the regression model. Through the simulation and verification of actual examples, the following conclusions are drawn:

I. From the perspective of the forecast model structure, economic growth is the main factor of energy consumption, and China's energy demand will still experience a period of high growth.

II. The prediction error of this study can reach about 1.35%, which is better than using the PSO and GA algorithms alone. It can more accurately predict the future total rural energy demand and guide the construction of the rural energy system.

III. This study standardizes the calculation process, strengthens the key influencing factors, can more accurately predict the total energy demand in rural areas, and provides support for the construction of rural energy systems.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

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Author contributions

WG was responsible for the specific work of this article. ZL and LT guided the work of this article. CH and WL did some calculations. WS, YJ, and LC collected data and calculated and compared the plans.

Acknowledgments

The corresponding author thanks Economic and Technology Institute, State Grid Fujian Electric Power Co., Ltd. and Tianjin Tianda Qiushi Electric Power High Technology Co., Ltd. for their selfless support. The authors acknowledge the funding of the State Grid Corporation of China's Science and Technology Project (JSB17202000260).

Conflict of interest

Authors LW, WS, YJ, and LC were employed by Tianjin Tianda Qiushi Electric Power High Technology Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 20 October 2022

ACCEPTED 02 November 2022

PUBLISHED 18 January 2023

CITATION

Li B, Li M, Yan S, Zhang Y, Shi B and Ye J
(2023), An optimal energy storage
system sizing determination for
improving the utilization and forecasting
accuracy of photovoltaic (PV)
power stations.
Front. Energy Res. 10:1074916.
doi: 10.3389/fenrg.2022.1074916

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An optimal energy storage system sizing determination for improving the utilization and forecasting accuracy of photovoltaic (PV) power stations

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As a new type of flexible regulation resource, energy storage systems not only smooth out the fluctuation of new energy generation but also track the generation scheduling combined with new energy power to enhance the reliability of new energy system operations. In recent years, installing energy storage for new on-grid energy power stations has become a basic requirement in China, but there is still a lack of relevant assessment strategies and techno-economic evaluation of the size determination of energy storage systems from the perspective of new energy power stations. Therefore, this paper starts from summarizing the role and configuration method of energy storage in new energy power stations and then proposes multidimensional evaluation indicators, including the solar curtailment rate, forecasting accuracy, and economics, which are taken as the optimization targets for configuring energy storage systems in PV power stations. Lastly, taking the operational data of a 4000 MWPV plant in Belgium, for example, we develop six scenarios with different ratios of energy storage capacity and further explore the impact of energy storage size on the solar curtailment rate, PV curtailment power, and economics. The method proposed in this paper is effective for the performance evaluation of large PV power stations with annual operating data, realizes the automatic analysis on the optimal size determination of energy storage system for PV power stations, and verifies the rationality of the principle for configuring energy storage for PV power stations in some regions of China.

KEYWORDS

PV power station, solar curtailment rate, forecasting accuracy, economic analysis, energy storage system sizing

Highlights

- 1) This paper starts by summarizing the role and configuration method of energy storage in new energy power station and then proposes a new evaluation index system, including the solar curtailment rate, forecasting accuracy, and economics, which are taken as the optimization targets for configuring energy storage system in PV power stations.
- 2) It calculates the forecasting accuracy of PV power and the penalty cost for each month in terms of penalty rules in a certain region, provides the specific algorithm process of energy storage sizing, and derives the simulation results.
- 3) The method proposed in this paper is applicable to the analysis of the operating characteristics of large PV power stations within the whole year and realizes the automatic analysis of the optimal scheme for the configuration with energy storage on PV power stations.

1 Introduction

In recent years, solar energy has been widely regarded as one of the largest green energy and plays a major role in modern power system (Ndebele, 2020). Combined with the “carbon peak and carbon neutral” target proposed by China (Qian et al., 2022), it is expected that by 2030, the installed capacity of domestic PV power generation will exceed 1000 GW (Kut et al., 2021). Meanwhile, by the end of 2021, the cumulative installed solar power capacity in Germany reached 66.5 GW and is expected to exceed 100 GW by 2030. In addition, Australia’s installed capacity has also reached 25.3 GW (Ali et al., 2019; Apeh et al., 2022).

However, there remain two major issues when integrating it into the power grid due to the consequent intermittent and fluctuating features (Chao, 2011; Kim et al., 2020). In addition, the grid dispatching center uses the forecasting power of the PV power station as reference for scheduling plan, but there is still a large deviation between forecasting power and actual generation (Keeratimahat et al., 2021), which may not only cause the occurrence of PV curtailment (Bird et al., 2016; Zhang et al., 2022a) but also result in low system reliability and security due to inadequate backup resources. Furthermore, it is possible to face high penalty for PV power station (Azimov and Avezova, 2022).

Energy storage is one of the most effective solutions to smooth out new energy power fluctuations (Chen et al., 2021; Yang et al., 2022), promote high penetration of grid-connected green energy, and reduce the forecasting deviations of PV power, because of its flexible dual characteristics of charging and discharging (Lutsenko and Fetsov, 2020). Therefore, the development of energy storage system will promote energy conservation and emission reduction (Lu et al., 2022). However, the initial investment cost of energy storage is high (Du et al., 2022), which makes it necessary to figure out a

reasonable configuring capacity. J. Li et al. (2020) propose a capacity optimization method for combined PV and storage systems, which considers the power allocation for PV and storage systems with the objective of economic optimality; P. D. Lund (2018) considered the PV self-consumption, as well as the sensitivity of the storage system size of weather, and finally obtained the economically optimal PV energy storage system configuration; R. Luthander et al. (2019) consider the matching of PV generation with demand and the transfer of solar energy through energy storage systems, which can achieve zero-energy buildings that meet the relevant requirements of EU regulations; and R. Domínguez et al. (2020) analyzed the operation and construction of the European power system in 2050 and proposed a stochastic model to study the future renewable energy construction planning. The results showed that new renewable energy generation capacity in Europe should reach 881 GW by 2050, taking into account the installation of energy storage system, and until then, CO₂ emissions will be reduced by 77%. F. Zhang et al. (2020a) proposed a predictive control strategy of energy storage system to improve AGC regulation capacity for high PV penetration system; meanwhile, a protective charging and discharging method is developed to extend energy storage system life. O. Alrawi et al. (2022) utilized empirical evidence and an economic model to evaluate rooftop PV systems in Qatar with different economic tools and collected real data, and S. Ud-Din Khan et al. (2022) developed theoretical models to evaluate the economy of integrated PV systems. Various types of lithium-ion and liquid-flow batteries are then evaluated technically and economically to determine appropriate type of storage. E. Oh and Son (2020), based on the uncertainty of wind power forecast, proposed a method of determining the theoretical energy storage capacity considering the stochastic characteristics of uncertainty. Finally, the effectiveness of the model is verified by the actual wind power generation data and the forecast data; V. Jani and H. Abdi (Jani and Abdi, 2018) established three different and incompatible objective functions considering operation cost, voltage deviation, and air emission to determine the optimal configuration of energy storage capacity. Two multiobjective hybrid algorithms are used to solve the problem. Simulation results show the effectiveness of the proposed method; S. Garip and S. Ozdemir (Garip and Ozdemir, 2022) chose energy cost minimization as the objective function. The proposed algorithm can obtain the optimal PV and energy storage size with minimum cost using the new energy management method and the PSO algorithm.

In summary, there have been many studies on energy storage sizing in PV power systems, but there are few sizing models with consideration of assessment indicators in terms of local new energy policy and economic factors. From the side of new energy generation, installing energy storage systems not only can improve the operating characteristics of PV power station but can also indirectly improve the system reliability and environmental protection. Therefore, this paper builds a new

energy storage sizing model for large PV power stations, with the aim to improve the solar curtailment rate and forecasting accuracy. First, with processing original data of PV power generation, the annual curtailment and forecasting accuracy of PV power are quantified. Then, we calculate the forecasting accuracy of PV power and the penalty cost for each month in terms of penalty rules in a certain region, provide the specific algorithm process of energy storage sizing, and derive the simulation results. A comprehensive energy storage system size determination strategy is obtained with the trade-off among the solar curtailment rate, the forecasting accuracy, and financial factors, which provides a practical reference to determine energy storage size for PV power station and further verifies the feasibility of energy storage system in the high PV penetration power system.

2 Role of energy storage in PV power stations and deployment rules in China

2.1 Roles of energy storage systems in PV power stations

Chinese renewable energy enters a new stage of high-quality leap; in the first half of 2022, nonfossil energy power generation accounted for 83% of new power generation installed capacity, while renewable energy generation exceeded 1.1 billion kW (Pablo-Romero et al., 2021). The generating capacity of hydropower, wind power, and solar power has increased by 20.3%, 7.8%, and 13.5% from the last year, respectively. Large-scale wind power and PV on-grid has posed a huge challenge to the safety and reliability of power system (Lei et al., 2022; Liu et al., 2022). From the perspective of system operation, installing energy storage not only mitigates PV power fluctuation but also realizes real-time scheduling of tracking power and enhance the grid's ability to consume new energy (Wang et al., 2019); in addition, the joint operation of PV power generation and energy storage can play the role of peak shaving and valley filling and also participate in auxiliary services (Motaleb et al., 2016). On the other side, from the perspective of new energy power plant, installing reasonably energy storage can improve the accuracy of PV forecasting (Liu et al., 2020), which may not only reduce the penalty cost but also further reduce the solar curtailment rate and improve net revenue of PV power station. In general, most optimization objectives of combining with PV power generation and energy storage focus on system operation, including meeting the technical requirements of grid power quality, minimizing power fluctuations, providing stable output power, and improving the utilization rate of new energy. With different optimization objectives, sizing procedures of energy storage system are developed, but the size determination strategy of energy storage systems from the perspective of renewable power

plant is not enough. The sizing of energy storage systems in PV power plants is closely related to the operation mode, market rules, and financial factors. Installing energy storage system with reasonable capacity is necessary for power plant operation; therefore, an optimal sizing strategy of energy storage system in PV power plants is very important and meaningful.

2.2 Deployment rules of energy storage in PV power stations in China

So far in 2021, the deployment rules of energy storage for new energy plant have been put forward in 24 provinces of China, of which governments have made clear requirements for energy storage supporting distributed PV. In all configuring rules of energy storage, the highest proportion of energy storage capacity requirements in Shandong Zaozhuang is 15%–30% of the installed PV rated capacity, and the duration time can be 2–4 h, while in some regions of Henan and Shanxi province the capacity of energy storage reaches 20%. Mostly the duration time is 2 h, and 3 h is required for the market-based on-grid project in Hebei province. We investigate the relevant rules in Jiangsu province in terms of energy storage capacity requirements, the solar curtailment rate, and the minimum standards for forecasting assessment. Specifically, Jiangsu Development and Reform Commission issued the “Provincial Development and Reform Commission on the province’s 2021 photovoltaic power generation project market notice”, in which the energy storage system with 8% of PV rated power generation and 2 h duration is needed principally for projects located in south of the Yangtze River; for those projects located in north of the Yangtze River, 10% of PV rated power and 2 h duration are required. In terms of the solar curtailment rate, according to the “Clean Energy Consumption Action Plan (2018–2020)” developed by the National Development and Reform Commission and the National Energy Administration, the utilization rate of PV power generation must be higher than 95% and the solar curtailment rate must be less than 5% (Zhang et al., 2022b). For assessment indicators, according to the specific requirements of the “Jiangsu Province Electricity Grid Operation Management Rules”, the time interval is set at 15 min, and the PV forecasting qualification rate is also defined in the rules. The criteria for qualification assessment are calculated monthly, and the penalty expense for every month is also standardized.

Based on aforementioned regulations and standards, this paper will figure out the economics of PV power plants with different sizes of energy storage systems. In order to calculate the relevant evaluation indicators from the massive dataset, this paper uses statistics to carry out the economic analysis of energy storage configuration scheme.

3 Statistical analysis and extraction of feature indicators with PV power station data processing

3.1 Solar curtailment rate

Through the statistics and analysis on the sample dataset of PV plant, the PV curtailment power at each sample point is measured, as shown in Eq. 1.

$$p_{s,i} = \max(0, p_{a,i} - p_{c,i}), \quad (1)$$

where $p_{s,i}$ is the PV curtailment power at the sampling point i , and I and $p_{c,i}$ are the actual and forecasting power at the sampling point i , respectively. When $p_{a,i} > p_{c,i}$, all of the PV power can be dispatched; when $p_{a,i} < p_{c,i}$, there is a surplus of PV power, and the phenomenon of solar curtailment occurs without energy storage system (Zhang et al., 2020b). By calculating the monthly curtailment power and solar curtailment rate (Fang et al., 2017), actual on-grid power of PV station in each month can be indirectly deduced. The total monthly solar curtailment power and solar curtailment rate is shown in Eqs 2, 3.

$$p_{s,m} = \sum_{i=1}^{96 \cdot d(m)} p_{s,i}, \quad (2)$$

where $p_{s,m}$ is the PV curtailment power dataset for each month, and $d(m)$ denotes the number of days at the month m .

$$\lambda(m) = \sum_{i=1}^{96 \cdot d(m)} \frac{p_{s,i}}{p_{a,i}}, \quad (3)$$

where $\lambda(m)$ denotes the dataset of solar curtailment rate in each month.

3.2 Forecasting qualification rate of PV power generation

3.2.1 Monthly forecasting qualification rate

According to “Jiangsu Province Electricity Grid Operation Management Rules,” the short- and medium-term PV forecasting power are computed by 96 points, and we obtain the qualification rate from Eq. 4. The next day qualification rate is required not less than 90%. The qualification rate of PV forecasting power is determined by the ratio of qualified points to total points for every month. When the unqualified rate exceeds 2%, PV power station will be punished by ¥10 per 10,000 kW of rated capacity.

$$\alpha(\%) = \left(1 - \frac{|p_{a,i} - p_{c,i}|}{C_{ap}} \right) \times 100\%, \quad (4)$$

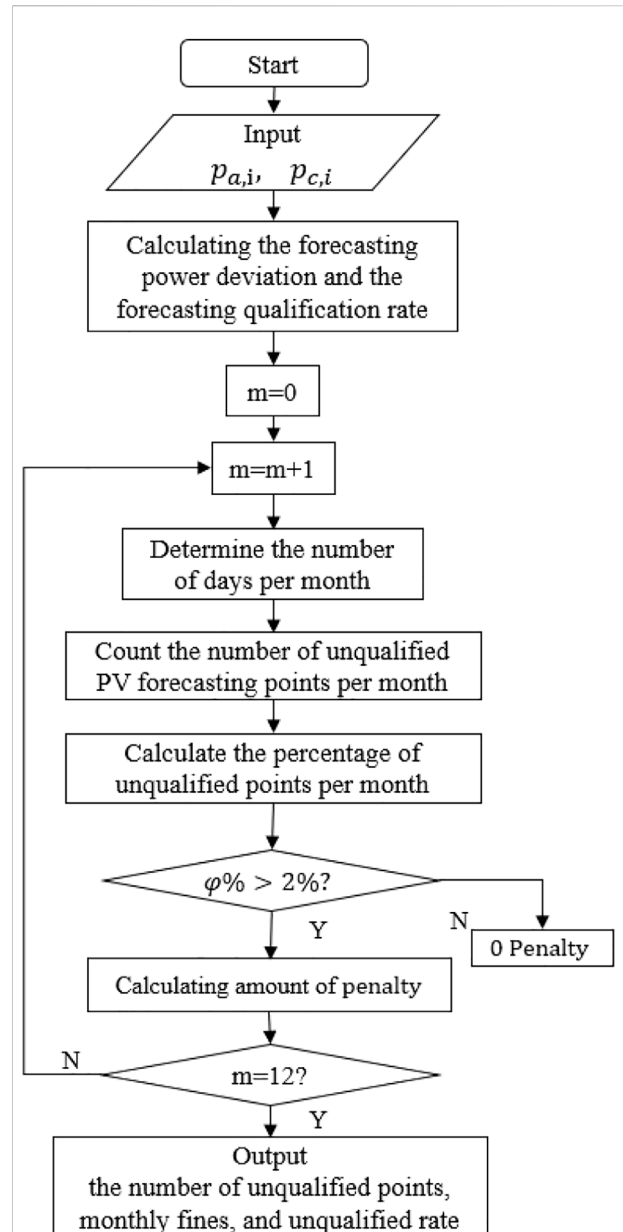


FIGURE 1
Statistical process of unqualified forecasting points for PV power station. The steps are as follows.

In Eq. 4, $p_{a,i}$ is the actual power at the sample point i , $p_{c,i}$ is the forecasted power at the sample point i , and C_{ap} is PV rated capacity.

3.2.2 Statistical analysis process

In order to statistically calculate the number of unqualified PV forecasting points from a huge dataset and quantified the penalty cost for each month, this paper proposes a method to count the monthly unqualified PV forecasting points and specify the penalty cost; the process is shown in Figure 1.

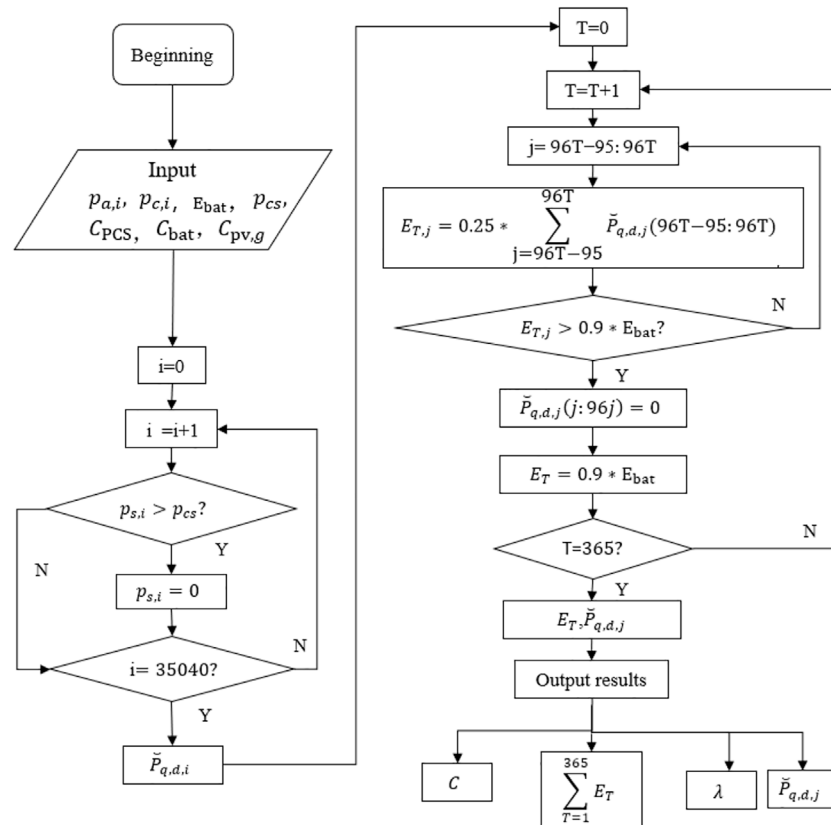


FIGURE 2

Implementation process of energy storage capacity size determination.

Step 1: Input data, calculate the forecasting power deviation and qualification rate for each point using Eq. 4.

Step 2: The number of sampling points for each month is calculated to determine the specific data range from each month's dataset, as shown in Eq. 5.

$$S(m) = \left[\sum_{i=1}^{m-1} 96 \times d(m-1) + 1, \sum_{i=1}^m 96 \times d(m) \right], \quad (5)$$

where $S(m)$ represents the specific data range corresponding to the data of month m in the annual dataset, and $d(m)$ represents the number of days in month m . When and only when $m = 1$, $\sum_{i=1}^{m-1} 96 \times d(m-1) = 0$.

Step 3: Count the number of unqualified PV forecasting points in each month as shown in equation 6, and calculate the percentage of unqualified points in each month as shown in Eq. 7.

$$N(m) = \{\alpha[S(m)] < 90\%\}, \quad (6)$$

$$\varphi(m) = \frac{N(m)}{\sum_{i=1}^m 96 \times d(m) - \sum_{i=1}^{m-1} 96 \times d(m-1)}, \quad (7)$$

where $N(m)$ is the number of unqualified points in month m , and $\alpha[S(m)]$ indicates the qualification rate in month m . In Eq. 7, $\varphi(m)$ is the percentage of monthly unqualified points.

Step 4: Determine whether the percentage of unqualified points is greater than 2% per month. If it is greater than 2%, calculate the monthly penalty, as shown in Eq. 8, and if less than or equal to 2%, the penalty is zero in the month.

Let $|p_{a,i} - p_{c,i}| = p_{p,i}$, then

$$C_d(m) = \sum_{i=1}^{96 \times d(m)} \sum_{i \in [(\alpha[S(m)] < 90\%) \cup (\varphi(m) > 2\%)]} p_{p,i} \times c_{ple}, \quad (8)$$

where $p_{p,i}$ denotes the absolute value of the PV forecasting deviation at the sample point i , $C_d(m)$ denotes the penalty in month m , and c_{ple} represents penalty cost of per unit unqualified forecasting PV power.

Step 5: Determine whether all of the monthly data have been analyzed, otherwise return to step 2.

Step 6: Output: calculation results including penalty and the number of unqualified points for each month.

TABLE 1 Set value of energy storage power and capacity.

The rated power ratio of energy storage with PV (%)	Power/MW	Duration/h	The energy storage system capacity/MWh
8	320	2	640
10	400	2	800
11	440	2	880
12	480	2	960
13	520	2	1,040
15	600	2	1,200

TABLE 2 Main parameter settings.

Parameter	Setting
The forecasting data and raw data of PV power	96*365,96*365
Rated power (p_{cs}),Capacity (E_{bat})	Configured at 8%–15% of installed PV capacity
Cost per unit capacity (C_{bat})	1.3¥/Wh
Cost per unit power (C_{PCS})	0.08¥/W
PV on-grid tariff ($C_{pv,g}$)	0.5¥/kWh

4 Sizing determination strategy of energy storage considering assessment indicators and financial factor

The sizing process of energy storage capacity is programmed with MATLAB, as shown in Figure 2. By extracting and processing the raw dataset after performing multiple cycles, the feature indicators mentioned in section 2 are developed.

The steps are as follows:

Step 1 Input basic dataset and initial parameters including energy storage capacity E_{bat} and rated power p_{cs} for different scenarios, cost per unit capacity C_{bat} , cost per unit power C_{PCS} , and PV on-grid tariff $C_{pv,g}$.

Step 2 Input power constraints, that is, when the first cycle is performed, the PV curtailment power of each sample point is calculated by Eq. 1 to form curtailment dataset that corresponds to each time point, and the curtailment power dataset is formed by Eq. 9 after filtering the adsorption by energy storage. If the curtailment power at a certain moment is greater than the rated power of energy storage, the power cannot be absorbed and set as zero; meanwhile, curtailment dataset is updated.

$$P_{q,d,i} = [p_{s,i}(p_{s,i} > p_{cs}) = 0] \cup [p_{s,i} \leq p_{cs}], i \in [1, 35040], \quad (9)$$

where $P_{q,d,i}$ is the PV curtailment dataset composed by consumption power of energy storage.

$$E_{T,j} = 0.25 * \sum_{j=96T-95}^{96T} P_{q,d,j} (96T - 95 \sim 96T), T \in [1, 365], j \in [96T - 95, 96T], \quad (10)$$

where $E_{T,j}$ is the total amount of PV curtailment power that has been consumed by the energy storage until sampling point j in day T .

Step 3 Energy constraints: the energy storage system is set one cycle per day; therefore, the dataset is converted from a scale of 96*365 to a scale of 1*365. Then the second cycle is carried out on the basis of the end of the first cycle, which takes into account whether the daily energy storage capacity reaches 90% of the rated capacity, and also tracks the real-time curtailment power being consumed at every 15 min sample point. The energy is calculated per day as shown in Eq. 10.

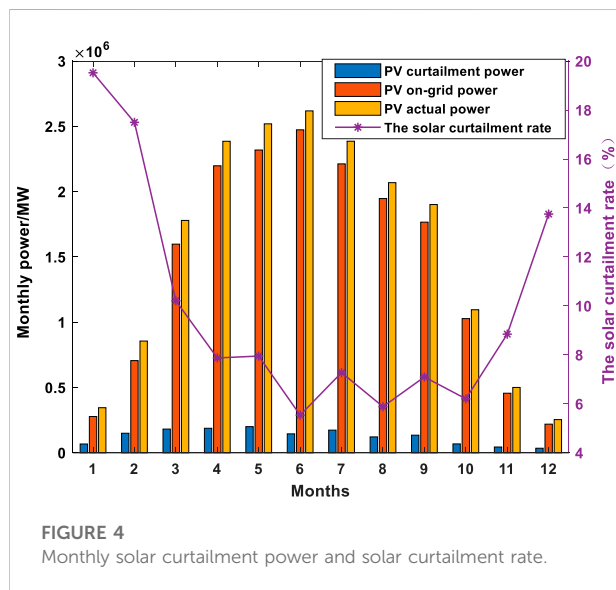
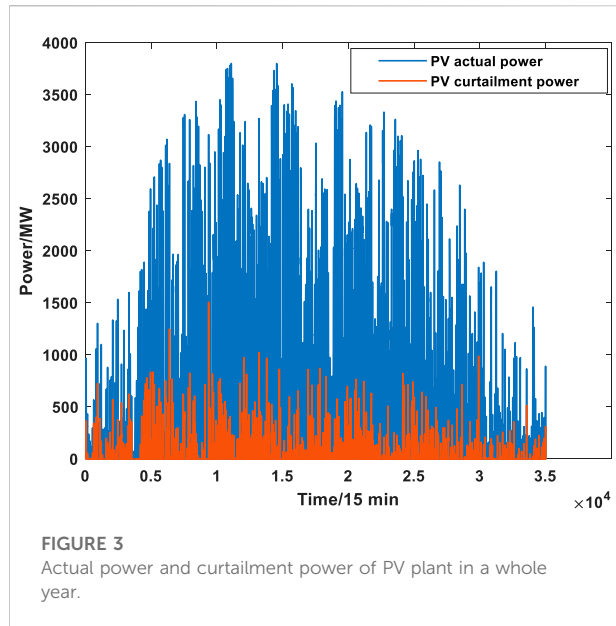
In order to extend the life of battery energy storage, the charging and discharging capacity limit is stipulated as 90% of the rated capacity. Therefore, when the storage charging energy is greater than 90% of the rated capacity, the storage capacity needs to be defaulted on the day.

$$E_{T,j} = 0.9 * E_{bat}, \quad (11)$$

$$P_{q,d,j} (j \sim 96T) = 0. \quad (12)$$

At this point, the energy storage battery has reached saturation after being completely charged during the day, and no longer absorbs the PV curtailment power; therefore, the real-time dataset of the solar curtailment power that can be absorbed by the battery is updated again.

Step 4 When all data are cycled through for 365 days in a year, the net revenue of energy storage C is obtained as shown in Eq. 13. The results of the solar curtailment rate, C , and the loss cost are outputted.

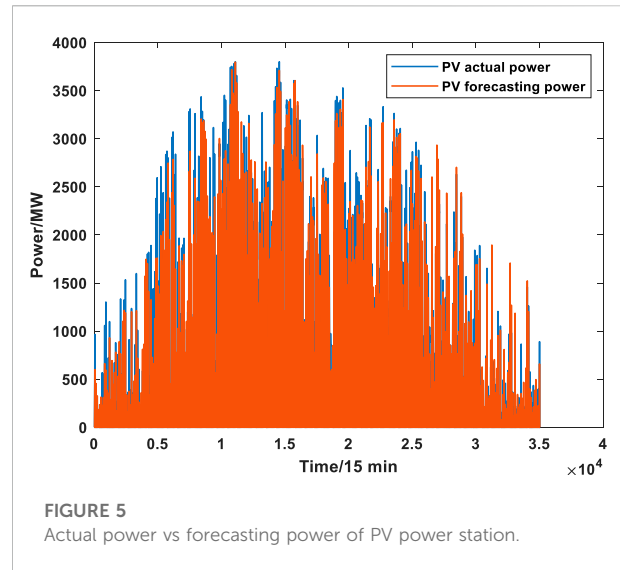


$$C = \sum_{T=1}^{365} E_{P,T} * C_{pv,g} - P_{cs} * C_{PCS} - E_{bat} * C_{bat} \quad (13)$$

5 Case studies

5.1 Basic data

In this paper, the original data of 35,040 sample points with an interval of 15 min for a 4000 MW PV plant in Belgium are used to study the size determination of energy storage. From the



rules mentioned in section 2.2, the energy storage capacity ratio is set as shown in Table 1.

From Table 1, six scenarios with energy storage power ratios of 8%, 10%, 11%, 12%, 13%, and 15% are built. To discuss the techno-economic indicators proposed in section 2, the initial parameters are described in Table 2.

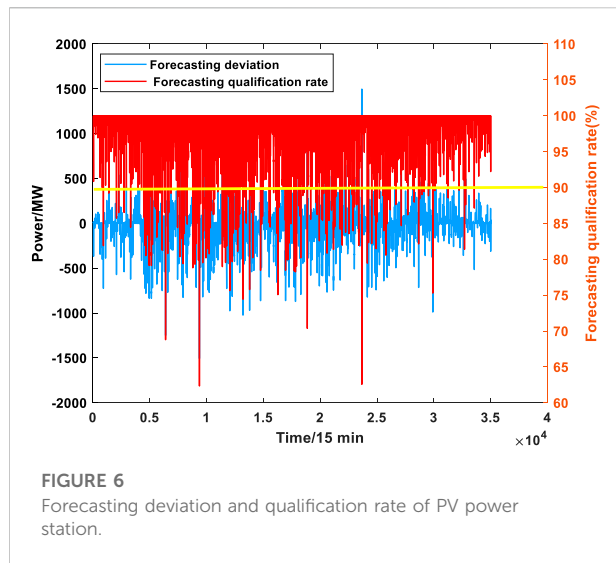
5.2 Analysis of feature indicators

The PV curtailment power of each sample point can be obtained from dataset by Eq. 1, and then the actual power and curtailment power of PV plant for the whole year is shown in Figure 3.

From Figure 3, it can be seen that the solar curtailment situation of the PV plant is quite serious. To further quantify the solar curtailment, the monthly solar curtailment power and solar curtailment rate are performed by Eqs 2, 3, respectively. Then, actual PV on-grid power for each month can be figured out, as shown in Figure 4.

In Figure 4, it is clear that the solar curtailment rate in January is as high as 19.5%, the lowest in June is only 5.5%, and the average solar curtailment rate is as high as 8.07%. The solar curtailment occurred with low forecasting accuracy at some time points, which can be alleviated by installing storage devices for PV power plant. To further investigate the impact of PV forecasting accuracy on solar curtailment rate, the actual power generated at each point is compared with the forecasting power of the previous day, as shown in Figure 5.

As can be seen in Figure 5, there are still many sample points with significant forecasting deviation. When dispatching power is too high, PV power cannot meet the load demand, and when dispatching power is too low, PV power generation is surplus. According to the regulation of “Jiangsu Province Electricity Grid Operation Management Rules,” the unqualified points of PV



forecasting power, the forecasting deviation, and the qualification rate of each sample point can be provided. The results are shown in Figure 6.

From Figure 6, it can be seen that the deviation between the forecasting and the actual power of some points is large, and there also exist many unqualified forecasting points.

5.3 Results and discussion

5.3.1 Simulation results

To get the total number of unqualified points for each month from the huge dataset and thus calculating penalty cost, the simulation results are outputted by completing steps one to six in section 3, as shown in Table 3.

TABLE 3 Statistics and simulation results.

Month no.	Day no.	Point no.	Monthly unqualified points number	Percentage of monthly unqualified point (%)	Whether $\geq 2\%$	The sum of unqualified predicted power(MW)	Penalty cost (¥10,000 unit)
1	31	2,976	42	1.4	N	—	0
2	28	2,688	166	6.18	Y	95,280	9.53
3	31	2,976	219	7.34	Y	130,702	13.07
4	30	2,880	348	12.08	Y	200,558	20.06
5	31	2,976	226	7.6	Y	127,955	12.8
6	30	2,880	208	7.2	Y	121,992	12.2
7	31	2,976	216	7.3	Y	127,626	12.76
8	31	2,976	178	6.0	Y	91,644	9.16
9	30	2,880	181	6.28	Y	110,362	11.04
10	31	2,976	48	1.6	N	—	0
11	30	2,880	29	1	N	—	0
12	31	2,976	31	1.04	N	—	0

From the results in Table 3, months of the forecasting power assessment in 2021 is unqualified, and the total penalty to be paid is about ¥1,006,200, which seriously affects the efficiency of system dispatching and causes additional expenses for the PV power plant. To solve this problem, energy storage system should be installed for PV power stations. The simulation results for six scenarios with different energy storage sizes are shown in Table 4.

To describe the effect of energy storage size on each assessment indicator, more discussions including the influence on the net income, the solar curtailment rate, and the forecasting qualification rate are developed.

5.3.2 Impact of energy storage capacity on net income

From the perspective of the net income of energy storage, with the increase of the storage capacity, the net income of energy storage shows a trend of first increase and then decrease, as shown in Figure 7. As we know, energy storage is charged when the PV power is in surplus and discharged at night, an increasing income present with the increase of power ratio, and the maximum annual net income reaches 3.17 million. However, when the power ratio exceeds 11%, the income begins to decline, and when the ratio exceeds by 12%, the income is even negative. With the increase of the storage capacity, the investment cost of energy storage rises and the income obtained from the PV consumption cannot offset the annual investment cost of energy storage, as shown in Figure 8.

5.3.3 Impact of energy storage capacity on the solar curtailment rate

When the power ratio is 8%, the annual solar curtailment rate is already lower than 5%. With the increase of the storage capacity, the solar curtailment rate decreased continuously

TABLE 4 Simulation results with different energy storage sizes.

The power ratio of energy storage with PV (%)	Power/MW	Capacity/MWh	Annual investment cost/¥10,000 unit	Annual solar curtailment reduction/MWh	Net income/¥10,000 unit	Solar curtailment rate		Annual unqualified point		Penalty/¥10,000 unit	
						Without energy storage	With energy storage	Without energy storage	With energy storage	Without energy storage	With energy storage
8	320	640	8,576	175,503	23.67	8.07%	4.32%	1892	1892	100.62	100.62
10	400	800	10,720	220,935	105.81	8.07%	3.34%	1892	1892	100.62	100.62
11	440	880	11,792	242,183	317.17	8.07%	2.89%	1892	1,689	100.62	92.52
12	480	960	12,864	260,905	181.25	8.07%	2.5%	1892	1,526	100.62	85.55
13	520	1,040	13,936	276,752	-98.37	8.07%	2.15%	1892	1,399	100.62	79.76
15	600	1,200	16,080	308,086	-675.7	8.07%	1.5%	1892	1,175	100.62	68.06

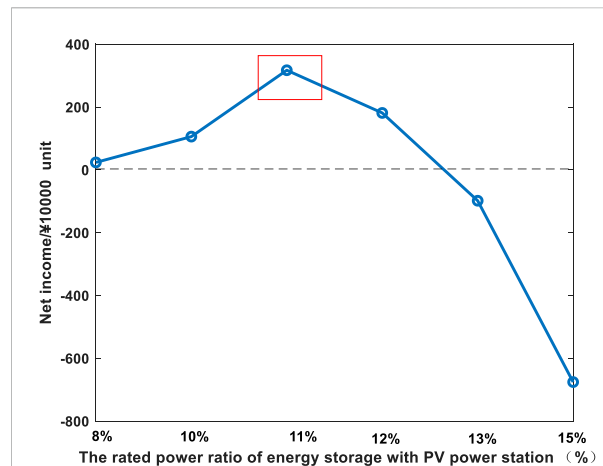


FIGURE 7

Net income of energy storage with different rated power ratios.

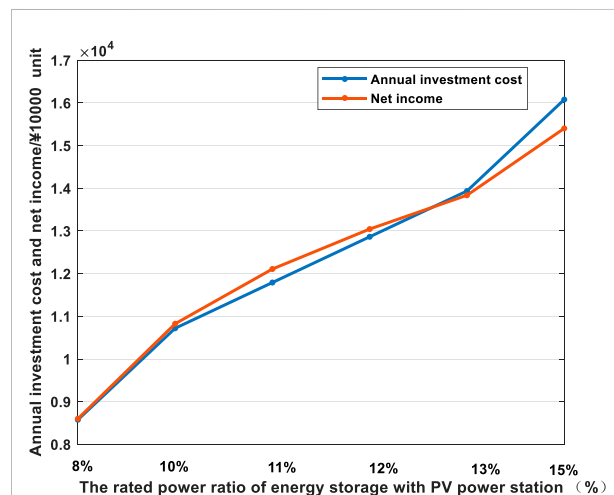


FIGURE 8

Net income and annual investment cost of energy storage.

from 4.32% to 1.5%, and the PV utilization rate is greatly improved, as shown in Figure 9. However, with the large size of energy storage, the net income of energy storage is negative when the power ratio exceeds 12% even the improvement of the PV consumption rate. Therefore, the size determination of energy storage should involve the solar curtailment rate and economics.

When the capacity ratio is 11% (440MW/880 MWh), the maximum net revenue of energy storage is obtained. Here, the solar curtailment rate is 2.89%, which is far below the specified value. The comparison of the solar curtailment power at each point without and with energy storage is shown in Figure 10. It is obvious for reducing the curtailment for PV power stations.

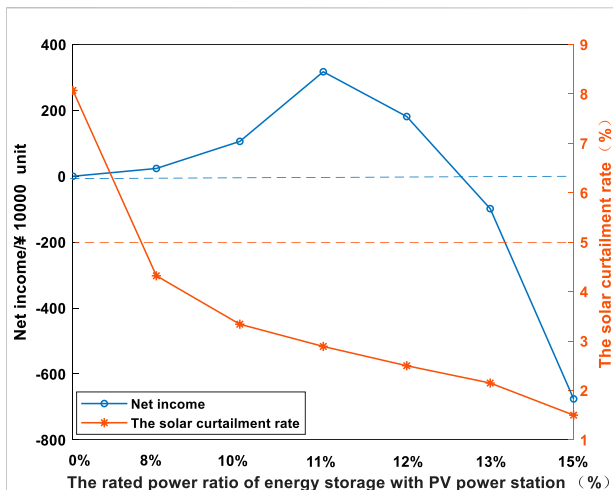


FIGURE 9

Solar curtailment rate and net income with different power ratios.

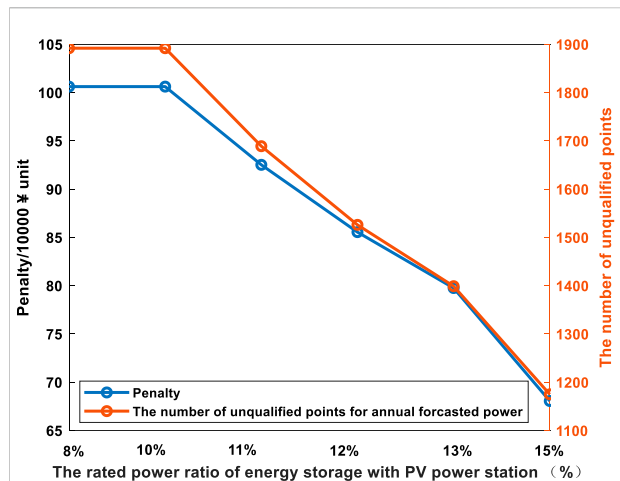


FIGURE 11

Annual unqualified forecasting power points and penalty with different rated power ratios.

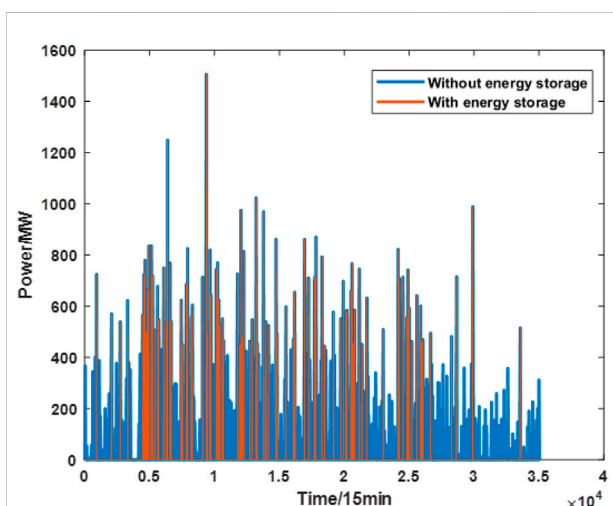


FIGURE 10

Solar curtailment power without and with energy storage.

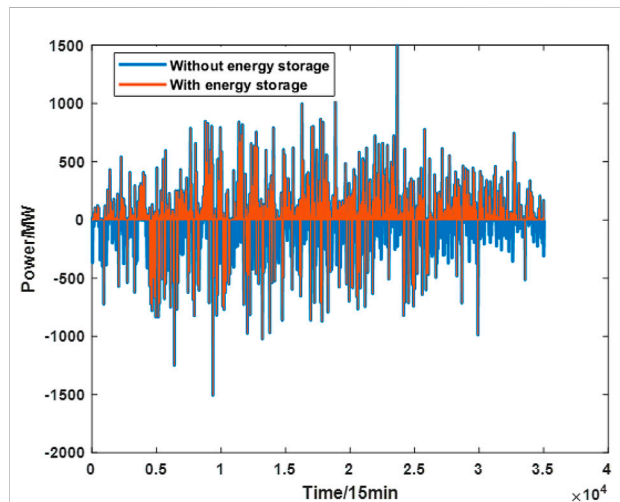


FIGURE 12

Deviation between forecasting and actual power.

5.3.4 Effect of energy storage capacity on the forecasting qualification rate

As the rated power ratio increases, the penalty and annual unqualified forecasting points decreases, as shown in Figure 11. The penalty remains the same level from 8% to 10%, and the number of annual unqualified forecasting points does not change, which means that the energy storage size is not enough.

The net income of energy storage does not increase continuously while improving the forecasting qualification rate and reducing the penalty, as seen in Figure 7. The net income is negative with the ratio of 13%. The highest income appears with the ratio of 11%; meanwhile, the penalty cost decreases by

¥81,000 and the unqualified forecasting point number drops by 203. When the ratio is 12%, the penalty cost and unqualified points reduction are ¥150,700 and 330, respectively. However, the net income is 1.36 million lower than that of 11%. Therefore, the reasonable capacity will be confirmed as 440MW/880 MWh. The deviation of forecasting power and actual power is clearly improved, as shown in Figure 12.

The aforementioned results show that the maximum annual net income and lower solar curtailment rate of 2.89% can be realized with 440MW/880 MWh energy storage. Also, in this scenario, the deviation of forecasting and actual power improved largely and the forecasting qualification rate enhanced clearly.

6 Conclusion

In view of the lack of relevant policies and comprehensive techno-economic indicators when configuring energy storage at the PV power station side, an optimal size determination strategy of energy storage is proposed by considering assessment indicators and the economics from the perspective of PV plant according to the “Assessment Rules for New Energy Grid Connection in Jiangsu Province of China” in this paper. The feature indicators are automatically extracted from the annual operation data of PV plant, and different scenarios are established for evaluating the reduction of solar curtailment rate and the improvement of forecasting accuracy. The methods proposed in this paper are verified step by step based on the dataset of PV power station, and the following conclusions are summarized from the simulation results.

- 1) Taking a 4400 MW PV plant in Belgium, as example, the results show that when the rated power ratio is 11%, the highest annual net income of energy storage can be achieved. The solar curtailment rate is reduced to 2.89%, and total number of annual unqualified points of PV forecasting power is reduced by 203, which can effectively reduce the penalty cost of PV power plants.
- 2) The method proposed in this paper is applicable to the extraction of the operating characteristics of large PV power stations within the whole year and realizes the automatic analysis of the optimal sizing of energy storage from the side of PV power station.
- 3) For specific PV power plant, the size of energy storage should be determined by multidimensional optimization combined with the annual operating characteristics of PV power plants and local assessment rules, in favor of improving the techno-economic indicators of the joint operation of PV power stations and energy storage.

In summary, the method proposed in this paper is reasonable for the performance evaluation of large PV power stations with annual operating data and realizes the automatic analysis of the optimal size determination of energy storage systems for PV power stations, which will provide a

generalized sizing method of energy storage for PV power stations in different regions.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material; further inquiries can be directed to the corresponding author.

Author contributions

BL: writing and editing, establishing the model, data collation and analysis, and first author. ML: data collation and reviewing. SY, YZ, and BS: survey. JY: writing and methodology, reviewing and editing, and corresponding author.

Funding

This work was supported by Technical Standard of Shanghai 2020 “Technology Innovation Action Plan” (20DZ2205400).

Conflict of interest

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OPEN ACCESS

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SPECIALTY SECTION
This article was submitted to Process and
Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 07 December 2022
ACCEPTED 28 December 2022
PUBLISHED 19 January 2023

CITATION
Yin H, Yang X, Zhang Y, Yang X, Guo W and
Lu J (2023), Distributionally robust
transactive control for active distribution
systems with SOP-connected multi-
microgrids.
Front. Energy Res. 10:1118106.
doi: 10.3389/fenrg.2022.1118106

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Distributionally robust transactive control for active distribution systems with SOP-connected multi-microgrids

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The increasing demand for distributed energy and active load increases the risk of voltage violations in active distribution systems. This paper proposes a distributionally robust transactive control method for local energy trading and network operation management of active distribution systems with interconnected microgrids. In particular, the emerging SOP technology is used for the flexible connection of the multi-microgrids (MMGs). First, the local energy interactive market between distribution network operator (DNO) and regional microgrids is constructed to simultaneously solve the economic and security problems of distribution networks considering the energy trading scenarios and various operational constraints. Then, the dual relaxation technique is used to transform the two-layer structure model into a single-layer model. Furthermore, the single-layer game model is further transformed into a two-stage distributed robust problem considering the uncertainties of load demand and renewable power outputs, and the second stage of the problem is decomposed into multiple parallel subproblems without dual information. Finally, numerical simulations on IEEE-33 test system verify the advantages and effectiveness of the proposed method.

KEYWORDS

energy trading market, network constraints, multi-region microgrid, distribution robustness, soft open point (SOP), active distribution system

1 Introduction

The improvement of renewable energy penetration has promoted the transformation of traditional distribution network to active distribution systems, which puts forward higher requirements for efficiency, flexibility and responsiveness of the system. MMGs are considered as an emerging network design in active distribution systems (Yang et al., 2020a; Xu et al., 2020). Information exchange and energy sharing can be achieved through flexible interconnection of MGs (Yang et al., 2020b). It has significant advantages in power loss reduction, operation cost saving, and system reliability enhancement. The existing researches on MGs often pursue the economic benefits of individual microgrid, merely considering this objective could undermine the operation performance by causing nodal voltage violations. Therefore, it is imperative to resolve the economic and operational problems of the active distribution systems with MMGs in a holistic manner through joint optimization of energy trading and system operation.

Recent efforts have focused on the transactive control method for active distribution systems with MMGs, which can be classified into two categories: direct control-based and local energy market-based methods. The control-based methods (Yang et al., 2020a; Zhou et al.,

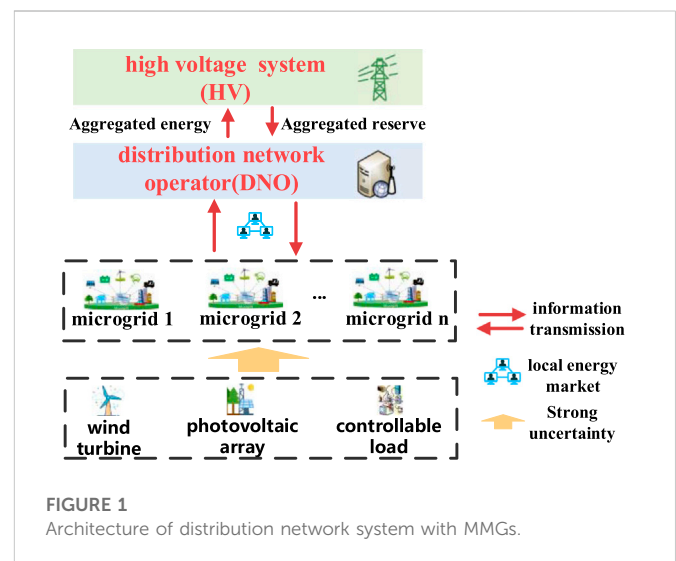
2020) are designed from the point of view of the DNO to determine direct control commands for all controllable parts by collecting all the information from MGs. Although this kind of methods are easy to be implemented, it has potential shortcomings such as poor scalability and low transparency, and it cannot give play to the flexibility of the users. The method based on the local energy market is different from the above method. This method ensures the consistency of control decisions by decentralized coordination of different entities in the distribution network (Yan et al., 2021). Thus, the regional microgrid can effectively manage the internal distributed energy, and protect the interests of the system (Liu et al., 2020). Recent studies about local energy markets mainly includes multiagent-based (Jadhav et al., 2019), game theory-based (Anoh et al., 2020), auction theory-based (El-Baz et al., 2019; Esfahani et al., 2019) methods, and semi-market-based method under supervision (Park et al., 2016). Although the above research provides a reference for building a local energy market, there are still many limitations.

- 1) Neglecting the joint research on the economic problems of multi-microgrid transactions and the technical problems of distribution network operation. The voltage regulation and the economy of the whole system may not play an optimal role simultaneously (Ji et al., 2019).
- 2) Neglecting the uncertainty of distributed energy and demand of users. The deviation between the result and the actual existence will increase, which will lead to improper regulation of physical components in the system. This situation not only makes the result of economic optimization deviate from the reality, but also may bring security problems to the distribution network system.

Therefore, an optimization model of energy interactive regulation based on the local energy market is constructed. This model can not only eliminate voltage violations, but also maximize the flexibility and economy of distribution network.

As for the interactive control of distribution network constraints, the early research mainly focused on resource management of microgrid and market clearing algorithm (Esfahani et al., 2019; Yang X et al., 2021). The interactive operation between agents is often ignored, and the application of SOP associated with energy trading has not been fully studied. As a new type of fully controlled power electronic device, SOP has fast response speed (Ji et al., 2019; Yang Z et al., 2021), and can accurately and continuously realize the characteristics of active/reactive power regulation of connected feeders (Yan et al., 2021). Therefore, this paper introduces SOP in the distribution system of local energy market to reduce the impact of distributed energy transactions on system power flow and improve the economy of the overall distribution network operation.

Secondly, as for how to effectively deal with the problem that the uncertainty of renewable energy and demand of users has a serious impact on the system (Park et al., 2016), the existing research schemes mainly include stochastic optimization (Liu et al., 2017; Guo et al., 2021), robust optimization (Zhao et al., 2020; Li et al., 2021) and distributed robust optimization (Wang et al., 2016; Liu et al., 2019; Ding et al., 2022). Among them, stochastic optimization depends on the known probability distribution, and it is easy to ignore the external influences such as risks and the characteristics of different internal



distributions, which will lead to too little consideration in decision-making. Although robust optimization only needs to use the set reflecting the change range of uncertain factors (Li et al., 2021), it only optimizes the goal in the worst case, which will lead to the result being too conservative and the income cannot reach the optimal value. Based on the above two methods, this paper uses the distributed robust optimization method to solve the optimal value under the uncertainty environment. The results obtained are robust while avoiding excessive conservatism.

The contributions of this work are summarized as follows:

- 1) A two-stage distributed robust energy trading regulation model is proposed for active distribution system. The two-level problem is decomposed into several parallel subproblems to avoid the need for dual information like traditional distributed robust optimization (DRO) according to the special two-phase scenario designed in this paper.
- 2) This paper considers various operation constraints, which is different from most existing researches that only focus on the transaction mechanism, and proposes a comprehensive decision-making method. SOP technology is introduced for flexible interconnection between multi-regional microgrids to actively improve system power flow and achieve security regulation of voltage and economic operation of transactions.
- 3) This paper uses KKT conditions, duality, linearization and relaxation techniques to transform the two-layer game problem into a single-layer MISOCP problem. In the case of many uncertain individuals as in this paper, this method is conducive to improving the efficiency of decision-making.

The rest of the paper is organized as follows. Section 2 introduces the transactive control architecture for active distribution systems with SOP-connected MMGs. In Section 3, the formulas of DNO and multi-microgrid optimization models and the conversion process of two-layer models are described in detail. The system uncertainty model based on distributed robustness is introduced in Section 4. In Section 5, the case study of interactive regulation architecture is introduced and discussed. Finally, conclusions are drawn in Section 6.

2 Proposed transactive control framework

The active distribution system with MMGs is built, as shown in Figure 1.

In this paper, the on-load tap changer (OLTC) is used to connect the distribution network with high voltage (HV) system, and the distribution network is divided into three regional microgrids. The regional microgrid includes distributed energy [mainly including photovoltaic array (PV) and wind turbine (WT)], energy storage system (ESS), general load and transferable load. SOPs are also used in the distribution network system to connect the regional microgrids, so as to conduct more accurate and rapid power regulation, and prevent transaction congestion.

Distribution network operator (DNO) is introduced as the intermediary between the HV and the regional microgrids, which is mainly responsible for the following: 1) Monitor and manage the operation of the distribution network to ensure that the system meets the constraints of safe operation and the stability of system voltage; 2) Different from other studies in which the microgrid directly trades with the HV, DNO is given the right to control and manage the trading volume between the distribution network and the HV, so that it can dynamically distribute the internal energy of the distribution network and improve the local energy consumption; 3) Participate in the local energy market between DNO and the regional microgrid, and dynamically adjust the clearing price by referring to the power demand of users, so as to minimize the operating cost.

As the main body participating in the local energy market on behalf of users, the regional microgrid is mainly responsible for the following: 1) Collect the electricity demand of all users in the region, and use it as a bargaining chip with DNO. The electricity demand is adjusted independently and flexibly to minimize the cost for users according to the clearing electricity price; 2) Manage the charging and discharging of energy storage systems to improve the local utilization rate of distributed energy.

In the transaction process of the local energy market, DNO needs to fully consider the dynamic feedback from users due to the price. Microgrids can decide their own power consumption strategy dynamically and flexibly according to the price (Lei et al., 2022). This process achieves the efficient operation of the overall system and improve the local consumption capacity of distributed energy (Xu et al., 2022). Furthermore, due to the uncertainty of distributed energy and load demand, there will be large deviation between the results obtained and the expected results, which will result in voltage deviation. In order to balance the interactive benefits and scheduling performance, this paper constructs a transactive control architecture for active distribution systems with SOP-connected MMGs.

3 Model formulation

3.1 Optimization model of DNO

For the DNO, its objective is to achieve power loss reduction and voltage regulation, and minimize the system operation cost. Therefore, the optimization model of the DNO can be expressed as follows.

$$\min F_{DNO}(x) = \alpha_o (f_{HV} + f_{loss} + f_{switch} - f_{MGs}) + \beta_v f_{voltage} \quad (1)$$

where α_o and β_v are the weight coefficients which can be determined by a subjective weighting method (Li et al., 2017). f_{loss} , f_{switch} , f_{HV} and f_{MGs} are the network losses cost, adjusting cost of OLTC, grid cost, and the income from MGs, respectively. $f_{voltage}$ represents accumulated voltage deviation, the specific expression above is as follows.

$$\begin{cases} f_{loss} = C_{loss} \left(\sum_{t=1}^T \sum_{ij \in \Omega_B} r_{ij} I_{t,ij}^2 + \sum_{t=1}^T \sum_{i=1}^N P_{t,i}^{SOP,loss} \right) \Delta t \\ f_{switch} = \sum_{ij \in \Omega_O} \sum_{t=1}^T (C_{OLTC} |K_{t,ij} - K_{t-1,ij}|) \\ f_{HV} = \sum_{t=1}^{N_T} \{ [g_t]^+ \gamma_t^b - [-g_t]^+ \gamma_t^s \} \Delta t \\ f_{MGs} = \sum_{t=1}^{N_T} \sum_{n=1}^{N_{mg}} \lambda_t P_{t,n}^{net} \Delta t \\ f_{voltage} = \sum_{t=1}^{N_T} \sum_{i=1}^{N_N} |U_{t,i}^2 - \bar{U}_{ref}^2| \end{cases} \quad (2)$$

where $[.]^+$ represents a projection operator on a non-negative orthogonal. For example, $[P]^+ = \max(P, 0)$.

1) Network constraints of the DN. The widely used *Distflow* branch model is adopted to model the DN as described in the following (Li et al., 2017; Cao et al., 2022).

$$\sum_{ik \in \Omega_i} P_{t,ik} - \sum_{ji \in \Omega_i} (P_{t,ji} - r_{ji} I_{t,ji}^2) = P_{t,i} \quad (3)$$

$$\sum_{ik \in \Omega_i} Q_{t,ik} - \sum_{ji \in \Omega_i} (Q_{t,ji} - x_{ji} I_{t,ji}^2) = Q_{t,i} \quad (4)$$

$$U_{t,i}^2 - U_{t,j}^2 - 2(r_{ij} P_{t,ij} + x_{ij} Q_{t,ij}) + (r_{ij}^2 + x_{ij}^2) I_{t,ij}^2 = 0 \quad (5)$$

$$I_{t,ij}^2 U_{t,i}^2 = P_{t,ij}^2 + Q_{t,ij}^2 \quad (6)$$

$$P_{t,i} = P_{t,i}^{PV} + P_{t,i}^{Wind} + P_{t,i}^{SOP} - P_{t,i}^L + (d_{t,i}^{ess} - c_{t,i}^{ess}) \quad (7)$$

$$Q_{t,i} = Q_{t,i}^{PV} + Q_{t,i}^{Wind} + Q_{t,i}^{SOP} - Q_{t,i}^L \quad (8)$$

$$Q_{t,i}^{PV} = P_{t,i}^{PV} \tan \theta_k^{PV} \quad (9)$$

$$\sqrt{(P_{t,i}^{PV})^2 + (Q_{t,i}^{PV})^2} \leq S_i^{PV} \quad (10)$$

The security constraints of the DN are presented as

$$\underline{U}^2 \leq U_{t,i}^2 \leq \bar{U}^2 \quad (11)$$

$$I_{t,ij}^2 \leq \bar{I}^2, \quad \forall t, (i, j) \in \Omega_l \quad (12)$$

Constraint Eq. 11) represents the system voltage limits, and Constraint Eq. 12) represents the maximum line current capacity.

2) SOP operation constraints. In this work, the back-to-back voltage source converters (VSCs)-based SOP device is utilized (Li et al., 2017). The optimization variables of the SOP consist of the active and reactive power outputs of the two VSCs, the relevant operational optimization constraints are as follows.

i) Active/reactive power constraints.

$$P_{t,i}^{SOP} + P_{t,j}^{SOP} + P_{t,i}^{SOP,loss} + P_{t,j}^{SOP,loss} = 0 \quad (13)$$

$$P_{t,i}^{SOP,loss} = A_i^{SOP} \sqrt{(P_{t,i}^{SOP})^2 + (Q_{t,i}^{SOP})^2} \quad (14)$$

$$\underline{Q}_i^{SOP} \leq Q_{t,i}^{SOP} \leq \bar{Q}_i^{SOP} \quad (15)$$

ii) Capacity constraints.

$$\sqrt{(P_{t,i}^{SOP})^2 + (Q_{t,i}^{SOP})^2} \leq S_i^{SOP} \quad (16)$$

3) Constraints of the OLTC.

The variables of the OLTC are considered as the action series of its tap steps. For the constraint formula of OLTC, this paper refers to (Li et al., 2017).

4) Transaction price constraint.

$$\lambda_t^{min} \leq \lambda_t \leq \lambda_t^{max} \quad (17)$$

$$\frac{1}{T} \sum_{t=1}^T \lambda_t \leq \frac{1}{T} \sum_{t=1}^T \lambda_t^{max} \quad (18)$$

Eq. (18) indicates that the average price of internal electric energy is not higher than the average price of power purchased from the superior grid to protect the interests of power users.

3.2 Optimization model of microgrids

The Multi-microgrid optimization model includes the power consumption plan of load demand in the trading market and the charging/discharging regulation of ESS. The optimization model of individual MG is given as follows.

$$\begin{aligned} \min F_{MG} &= \sum_{t=1}^{N_T} \lambda_t P_{t,n}^{net} \Delta t - \sum_{t=1}^{N_T} \sum_{i \in S_n} v_n^D (P_{t,i}^{L,down} + P_{t,i}^{L,up}) \Delta t + \sum_{\forall i} \sum_{e=1}^{N_e} \left(C_{deg} P_{t,i}^{ess,c} \eta^{ess,c} + \frac{P_{t,i}^{ess,d}}{\eta^{ess,d}} \right) \Delta t \\ s.t. P_{t,n}^{net} &= \sum_{i \in S_n} (P_{t,i}^{L,unc} + P_{t,i}^{L,up} + P_{t,i}^{L,do}) - P_{t,i}^{PV} + \sum_{e=1}^{N_e} (c_{t,e}^{ess} - d_{t,e}^{ess}) \end{aligned} \quad (19)$$

In Eq. (19), the first part represents the total cost of trading with DNO, the second part represents the dissatisfaction with the transferable load, and the third part represents the compensation cost for ESS aging and degradation. v_n^D is the inconvenience sensitivity coefficient of MG n (Yang et al., 2019), $v_n^D \geq 0$.

This paper refers to (Xu et al., 2019; Yang X et al., 2021) for the constraints of the charging/discharging power and charging state of ESS. Similarly, the constraint conditions of demand response (DR) refer to (Yang et al., 2019).

3.3 Transformation of the bilevel model

The decision optimization of DNO and microgrids is a two-layer optimization, which can be solved through Stackelberg game. The regional microgrid determines the operation status and the power exchange according to the received electricity price. The power exchange must meet the network constraints and match the optimal solution of the microgrids. This requires an iterative process to obtain the equilibrium solution

Compared with the iterative solution of traditional two-layer game, this paper considers that the decision-making optimization of the game is affected by uncertain factors and the convergence of regional microgrids is asynchronous. In order to get the optimization results more quickly and effectively, the two-layer optimization problem is transformed into a single-layer optimization problem by constructing Lagrangian functions and using KKT conditions and dual theory (Jin et al., 2021).

Because there are complementary constraints in the microgrids, such as the energy storage system cannot discharge and charge simultaneously, the relevant non-linear constraints are complementary relaxed. Finally, the following single-layer master-slave game problem can be obtained.

$$\begin{aligned} \min F_{lequ} &= \left\{ \alpha_0 \left(f_{HV} - \sum_t \sum_n \sum_{i \in S_n} (P_{t,i}^{L,fix} - P_{t,i}^{PV} - P_{t,i}^{wind}) \Delta t + f_{loss} + f_{switch} \right) + \beta_v F_{voltage} \right\} \\ &+ \sum_t \sum_i \left\{ \sum_e \left([-\mu_{2,t,i}^{L,up} L_{t,i}^{max} - \mu_{2,t,i}^{L,down} L_{t,i}^{max}] - \mu_{2,t,e}^{ess,c} P_e^{c,rat} - \mu_{2,t,e}^{ess,d} P_e^{d,rat} \right. \right. \\ &\left. \left. + \mu_{1,t,e}^{ess} S_e^{min} - \mu_{2,t,e}^L S_e^{max} \right) \right\} \end{aligned} \quad (20)$$

s.t. Eqs. 3–18

$$0 \leq \mu \perp h(x) \geq 0 \quad (21)$$

In Eq. (20), decision variables are λ_t , $K_{t,i,j}$, $P_{t,i}^{SOP}$, $Q_{t,i}^{SOP}$, $P_{t,i}^{L,up}$, $P_{t,i}^{L,down}$, $P_{t,i}^{ess,c}$, $P_{t,i}^{ess,d}$. The decision variables of DNO include clearing electricity price λ_t , the regulation of OLTC $K_{t,i,j}$, the active/reactive power of SOP in each period $P_{t,i}^{SOP}/Q_{t,i}^{SOP}$. The decision variables of microgrids include the load demand of DR $P_{t,i}^{L,up}/P_{t,i}^{L,down}$, and charging and discharging power of ESS in each period $P_{t,i}^{ess,c}/P_{t,i}^{ess,d}$.

4 Reformulation based on distributed robustness

4.1 Distributed robust model

Multi-scenario method is used to describe the uncertainty of load, PV and WT. The above deterministic optimization model (i.e., Eq. (20)) is transformed into uncertain model. The conversion result is as follows.

$$\begin{aligned} \min \mathbb{E}_\pi [\mathcal{J}_D] &= \sum_{\omega \in N_\omega} p_\omega F_{lequ,\omega} \\ &= \sum_{\omega \in N_\omega} p_\omega \times \left\{ \alpha_0 \left(f_{HV,\omega} - \sum_t \sum_n \sum_{i \in S_n} (P_{t,i,\omega}^{L,fix} - P_{t,i,\omega}^{PV} - P_{t,i,\omega}^{wind}) \Delta t + f_{loss,\omega} + f_{switch,\omega} \right) \right. \\ &\quad \left. + \beta_v F_{voltage,\omega} \right\} + \sum_t \sum_i \left\{ [-\mu_{2,t,i,\omega}^{L,up} L_{t,i}^{max} - \mu_{2,t,i,\omega}^{L,down} L_{t,i}^{max}] \right. \\ &\quad \left. + \sum_e (-\mu_{2,t,e,\omega}^{ess,c} P_e^{c,rat} - \mu_{2,t,e,\omega}^{ess,d} P_e^{d,rat} + \mu_{1,t,e,\omega}^{ess} S_e^{min} - \mu_{2,t,e,\omega}^L S_e^{max}) \right\} \end{aligned} \quad (22)$$

Discrete adjustment variables, such as OLTC's tap steps, are set as the first stage variables z according to the flexibility and real-time of the adjustment of each resource equipment, other continuous variables, such as active and reactive power of SOP, clearing electricity price and transferable load power, are set as variables in the second stage x_ω . The following functions can be obtained.

$$\begin{aligned} \min \mathbb{E}_\pi [\mathcal{J}_D] &= \\ \min_z \max_{p_\omega \in \Omega^p} \sum_{\omega \in N_\omega} p_\omega \min_{x_\omega} &\left\{ \alpha_0 \left(f_{HV,\omega} - \sum_t \sum_n \sum_{i \in S_n} (P_{t,i,\omega}^{L,fix} - P_{t,i,\omega}^{PV} - P_{t,i,\omega}^{wind}) \Delta t \right. \right. \\ &\quad \left. \left. + f_{loss,\omega} + f_{switch,\omega} \right) + \beta_v F_{voltage,\omega} \right\} \\ &+ \sum_t \sum_i \left\{ [-\mu_{2,t,i,\omega}^{L,up} L_{t,i}^{max} - \mu_{2,t,i,\omega}^{L,down} L_{t,i}^{max}] + \sum_e (-\mu_{2,t,e,\omega}^{ess,c} P_e^{c,rat} - \mu_{2,t,e,\omega}^{ess,d} P_e^{d,rat} \right. \\ &\quad \left. + \mu_{1,t,e,\omega}^{ess} S_e^{min} - \mu_{2,t,e,\omega}^L S_e^{max}) \right\} \end{aligned} \quad (23)$$

In order to ensure that the probability distribution of each scenario from historical data is close to the actual operation scenario, the uncertainty set of probability distribution is constructed by using the comprehensive method of norm-1 and norm-inf to limit the allowable

TABLE 1 PROCEDURE of modified C&CG ALGORITHM.

Algorithm 1 modified C&CG algorithm
1: Initialization: set $LB = -\infty$, $UB = +\infty$, $m = 0$, and tolerance ε . Get initial worst-case probability p_ω^0 through scenario generation method
While $UB - LB > \varepsilon$ do
2: Obtain the worst-case probability p_ω^{m*} , solve the master problem (35)–(40). Derive an optimal solution z^* and $(G^*, x^{1*}, \dots, x^{m*})$ and update $LB = \max\{LB, G^*\}$
3: Fix z^* , solve the subproblem (41)–(42) in parallel, yielding an optimal value $f(z^*)$ and worst-case probability p_ω^{m*} . Update $UB = \min\{UB, f(z^*)\}$
If $f(z^*)$ are feasible then
4: Create variables x_ω^m and add the new constraints to master problem
Update $m = m + 1$
End while

Remark 1: Compared with the existing methods, this paper optimizes the operation and economic performance of the local energy trading market, including the use of flexible components-SOPs, and the design of the modified DRO, to improve the overall operating flexibility of the system. The novelties of proposed regulation method are summarized as follows.

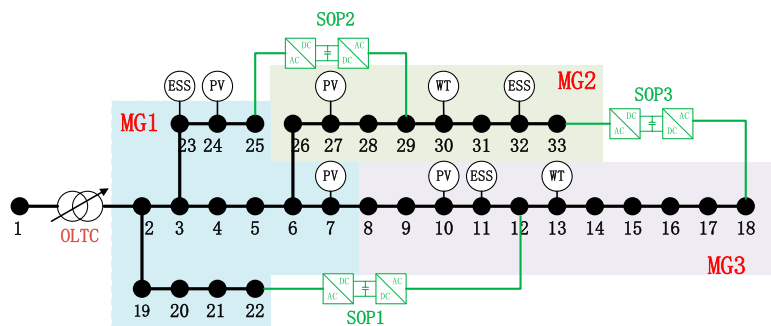


FIGURE 2

Topology diagram of the IEEE 33-bus test system with three microgrids and three SOPs.

fluctuation range of the probability distribution of discrete scenarios.

The uncertainty set is as follows.

$$\psi = \left\{ p_\omega \mid \begin{array}{l} p_\omega \geq 0 \\ \sum_{\omega=1}^{N_\omega} p_\omega = 1 \\ \sum_{\omega=1}^{N_\omega} |p_\omega - p_\omega^0| \leq \delta_1 \\ \max_{1 \leq \omega \leq N_\omega} |p_\omega - p_\omega^0| \leq \delta_\infty \end{array} \right\} \quad (24)$$

$$\begin{cases} \delta_1 = \frac{N_\omega}{2K} \ln \frac{2N_\omega}{1 - \alpha_1} \\ \delta_\infty = \frac{1}{2K} \ln \frac{2N_\omega}{1 - \alpha_\infty} \end{cases} \quad (25)$$

Eq. (24) and Eq. (25) are the comprehensive constraints of norm-1 and norm-inf.

4.2 Model linearization and cone relaxation transformation

1) Linearization. The Boolean variable κ is introduced to transform the complementary relaxation constraint in Eq. (21) into a linear inequality. The form is as follows.

2) Cone relaxation. Eq. (6) can be transformed into a second-order cone constraint through convex relaxation. The transformed equality constraint is as follows.

$$0 \leq \mu \leq M\kappa \quad (26)$$

$$0 \leq h(x) \leq M(I - \kappa) \quad (27)$$

Furthermore, variable replacement is used for linearization, that is, $l_{t,j}$ and $v_{t,j}$ are used to replace $I_{t,j}^2$ and $U_{t,j}^2$ in Eq. (3)–(5), (11) and (12), respectively; The non-linear voltage deviation term in Eq. (2) is replaced by the auxiliary variable $Aux_{t,j}$. The specific process is shown in (Li et al., 2017).

Because of the absolute value constraint in Eq. (24), the auxiliary variables z_ω^+ and z_ω^- are introduced to linearize the norm-1 constraint. The norm-inf constraint is linearized, similarly. The obtained linear constraint conditions are as follows.

$$z_\omega^+ + z_\omega^- \leq 1, \forall \omega \quad (28)$$

$$\begin{cases} 0 \leq p_\omega^+ \leq z_\omega^+ \delta_1, \forall \omega \\ 0 \leq p_\omega^- \leq z_\omega^- \delta_1, \forall \omega \\ p_\omega = p_\omega^0 + p_\omega^+ - p_\omega^-, \forall \omega \end{cases} \quad (29)$$

$$\sum_{\omega=1}^{N_\omega} (p_\omega^+ + p_\omega^-) \leq \delta_1 \quad (30)$$

$$p_\omega^+ + p_\omega^- \leq \delta_\infty, \forall \omega \quad (31)$$

TABLE 2 Relevant parameters of IEEE 33 bus test system.

Device	Location	Entity	Parameter
PV unit	Bus 7	MG3	500 kW
	Bus 10	MG3	500 kW
	Bus 24	MG1	400 kW
	Bus 27	MG2	400 kW
WT unit	Bus 13	MG3	1200 kW
	Bus 30	MG2	1000 kW
Energy storage	Bus 11	MG3	1.0 MWh, 0.2MW, .95
	Bus 23	MG1	1.0 MWh, 0.2MW, .95
	Bus 32	MG2	1.0 MWh,0.2 MW,0.95
SOPs	Buses 12-22, 25-29, 18-33	DN	Capacity: 1.0WVA
OLTC	Bus 1-2	DN	$\pm 5 \times 1\%$ (include $0\% \times 1\%$)

$$\left\| \begin{matrix} 2P_{t,ij} \\ 2Q_{t,ij} \\ l_{t,ij} - v_{t,i} \end{matrix} \right\|_2 \leq l_{t,ij} + v_{t,ij}, \forall t \quad (32)$$

$$(P_{t,i}^{\text{SOP}})^2 + (Q_{t,i}^{\text{SOP}})^2 \leq 2 \frac{P_{t,i}^{\text{SOP,loss}}}{\sqrt{2}A_i^{\text{SOP}}} \frac{P_{t,i}^{\text{SOP,loss}}}{\sqrt{2}A_i^{\text{SOP}}} \quad (33)$$

$$(P_{t,i}^{\text{alt}})^2 + (Q_{t,i}^{\text{alt}})^2 \leq 2 \frac{S_{t,i}^{\text{alt}}}{\sqrt{2}} \frac{S_{t,i}^{\text{alt}}}{\sqrt{2}}, \text{alt} \in \{\text{SOP}, \text{PV}, \text{wind}\} \quad (34)$$

Through above transformation processes, the non-linear programming problem is transformed into MISOCP model, which can be effectively solved by optimization solver (such as Gurobi and CPLEX).

4.3 Distributed robust model solving

Eq. (23) is a min-max-min three-layer two-stage model. Columns and constraints generation (C&CG) algorithm is used for iterative solution (Li et al., 2022).

The main problem is to solve the first stage optimal solution z^* and provide the updated lower bound value under the condition that the worst probability distribution is known. The matrix vector form of the original formula is used for the convenience of expression. The expression is as follows.

$$\min_{z \in Z, x \in X^s, G} G \quad (35)$$

$$G \geq \sum_{\omega=1}^{N_{\omega}} p_{\omega}^{m*} A^T x_{\omega}^m, \forall r = 1, 2, \dots, M \quad (36)$$

$$Cx_{\omega}^m \leq y \quad (37)$$

$$Ex_{\omega}^m = u \quad (38)$$

$$\|Q_i x_{\omega}^m + H_i\|_2 \leq c_i^T x_{\omega}^m + \rho_i \quad (39)$$

$$Dx_{\omega}^m + Fz = f \quad (40)$$

where $\sum_{\omega=1}^{N_{\omega}} p_{\omega}^{m*} A^T x_{\omega}^m$ represents the max-min part of Eq. (23); $A, C, E, D, F, Q, H, c, y, u, \rho, f$ represent the matrix or vector forms of the corresponding models; Eq. (37) and (38) represent the relevant constraints of variables in the second stage; Eq. (39) represents the second-order cone relaxation constraints; Eq. (40) represents the coupling constraints in the first stage and the second stage.

The subproblem solves the worst probability distribution value p_{ω}^{m*} of each scenario based on the z^* given by the main problem, and provides the updated upper bound value. The subproblem expression is as follows.

$$\max_{p_{\omega} \in \Omega^p} \min_{x_{\omega}} \sum_{\omega=1}^{N_{\omega}} p_{\omega}^m A^T x_{\omega}^m \quad (41)$$

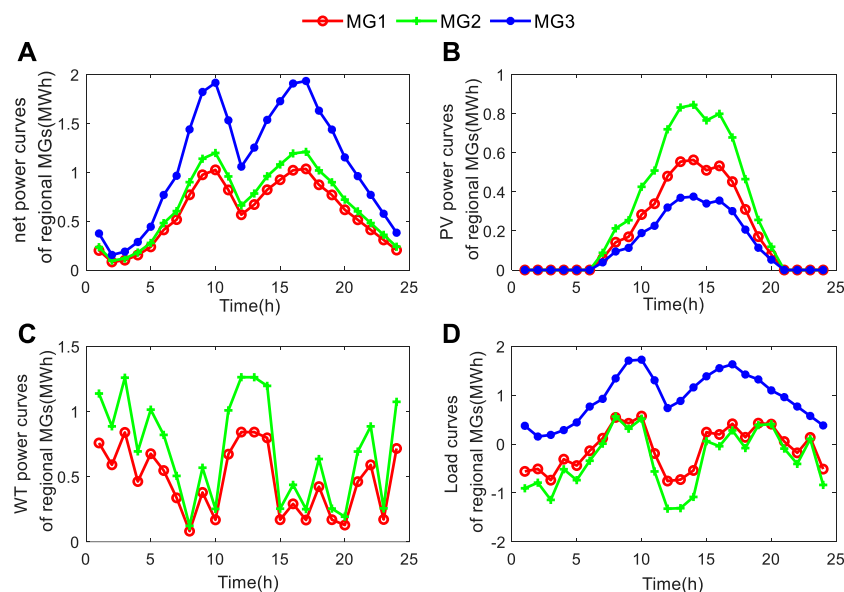
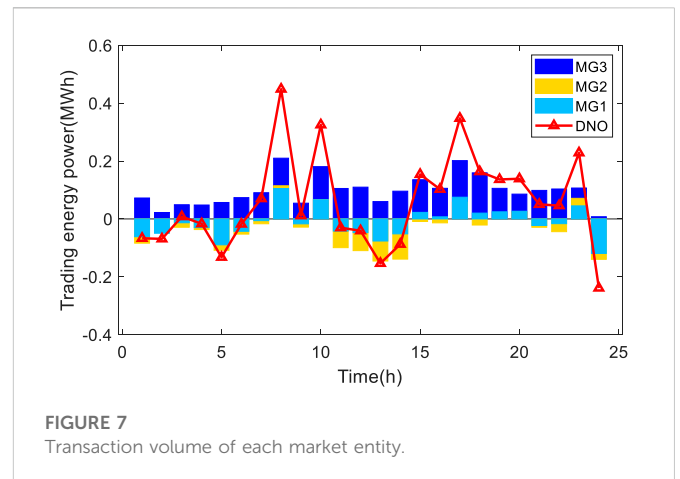
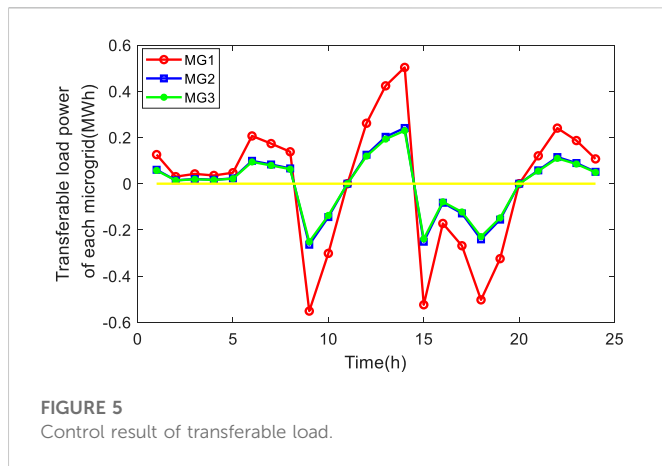
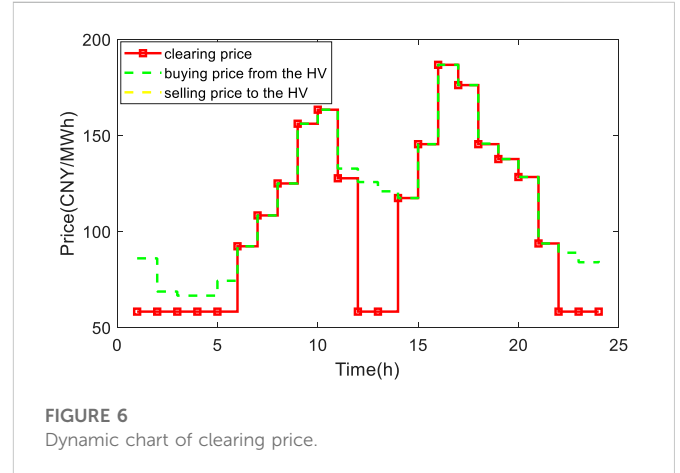
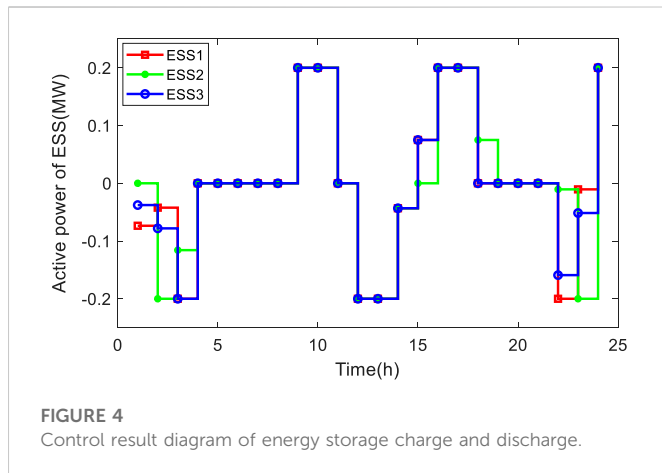


FIGURE 3

Initial data of microgrid in each region: (A) Total load of microgrid in each region; (B) Photovoltaic output of microgrid in each region; (C) Output of microgrid fans in each region; (D) Net load of microgrid in each region.



It can be judged that each scenario in the second stage is independent of each other, and the probability distribution values and variables are independent of each other according to the structural characteristics and scenario characteristics of the subproblem. The subproblem can be divided into two parts. The expression is as follows.

$$\begin{cases} f_{\omega} = \min_{x_{\omega}} A^T x_{\omega}^m \\ \max_{p_{\omega} \in \Omega^p} \sum_{\omega=1}^{N_{\omega}} p_{\omega}^m f_{\omega} \end{cases} \quad (42)$$

If Eq. (42) has a feasible solution, a group of additional variables x_{ω}^m and related constraints need to be generated and added to the main problem of the next iteration (Ding et al., 2018). The specific iterative solution process is shown in Table 1.

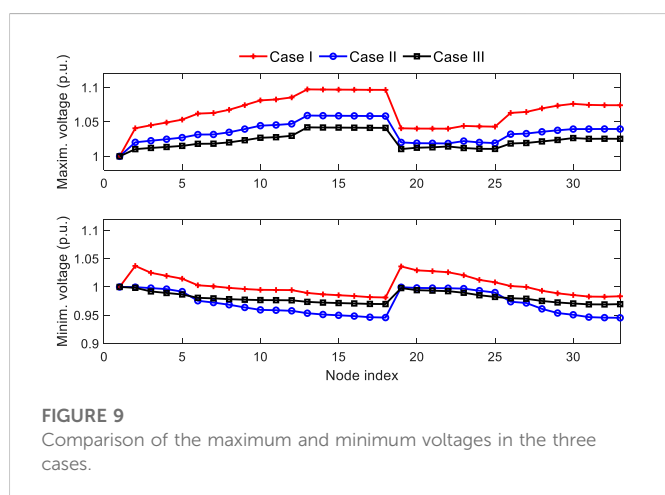
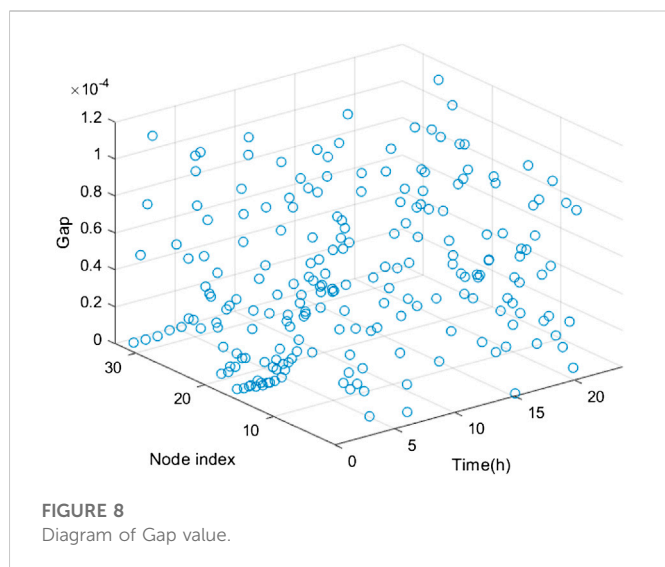
- 1) It is high efficiency. The transformation of two-stage game model and the use of the modified DRO method avoid mutual coupling factors and improve the overall decision efficiency.
- 2) It has better robustness and economy. It can improve power flow distribution, achieve voltage and reactive power regulation, and take into account the overall interests of the active distribution systems in a flexible trading market.

5 Simulation studies

5.1 Base data

In this paper, IEEE-33 node system is used for testing, which is divided into three regional microgrids (Li and Xu, 2019; Zhou et al., 2019; Li et al., 2020) as shown in Figure 2.

The whole system includes four PVs, two WTs, three ESSs and three SOPs. The relevant parameters are shown in Table 2. The loads of the microgrid in each region, the output of PVs and WTs, and the net loads are shown in Figure 3. The capacity of the installed SOPs is set as 1.0 MVA. The percentage of demands that participates the DR is assumed to be 20% (Yang et al., 2019; Cruz et al., 2020). The price of electricity purchased by the distribution network from the HV is set according to the reference (Jin et al., 2021), and the selling price of the distribution network is set at 400 ¥/MWh. $\lambda_t^{\min}$ is equal to the price of electricity sold by the active distribution systems to the HV. $\lambda_t^{\max}$ is equal to the price of electricity purchased by the active distribution systems from the HV. All the installed renewable generators are operated at a unit power factor without considering the localized reactive power support of renewables (Yang Z et al., 2021). Δt is set to 1 h. Referring to the setting in (Li et al., 2017), α_o and β_v are set to .833 and .167, respectively; the limiting voltages $\bar{U}/U$ are set to 1.05 p.u. and .95 p.u.; the correlation coefficient of network loss



C_{loss} is set to .08; the charging and discharging coefficient of ESS C_{deg} is set to 18.741 ¥/MWh; the allowable operation number of OLTC $\bar{\Delta}^{OLTC}$ is set to 4 times/day; and the initial tap step $k_{ij,0}$ and tap step increment Δk_{ij} are set to 1.0% and 1%, respectively. The proposed method in this paper was implemented in the YALMIP optimization toolbox with MATLAB R2020a, and solved by GUROBI 9.1.2.

5.2 Results and analysis

5.2.1 Impact analysis of local energy interaction market

The energy storage system charging/discharging control and the transferable load control are important regulation means for microgrids to respond the DNO's decision in local interactive market. The results are shown in Figure 4 and Figure 5, respectively.

In the local interactive market, the price of electricity acts as a "bridge" for DNO to transfer its decisions to the microgrids. The transaction price is shown in Figure 6. The transaction volume of the microgrids is shown in Figure 7.

TABLE 3 Comparison results under different cases.

System performance	Case I	Case II	Case III
Line power losses (kWh)	794.771	1486.419	784.708
SOP power losses (kWh)	481.468	—	478.863
Voltage deviation (p.u.)	58.729	28.064	16.531
Target value of DNO	339.678	562.562	456.998
Total cost of MGs (¥)	2148.485	2374.229	2158.872

Figures 4–7 show that the power generation of renewable energy does not reach the peak, and the supply is less than the demand, which makes the electricity price rise continuously in the peak period of power consumption (6:00–10:00 and 15:00–20:00). Therefore, users have to dynamically adjust their own power consumption strategy (i.e., ESS discharge, load demand decreases) to maintain their own interests in this period of time; The supply exceeds the demand, the microgrid's own power generation can meet the demand, and DNO does not need to purchase power from the HV in the low peak period of power consumption (0:00–6:00) and the peak period of renewable energy power generation (11:00–14:00). This situation makes the electricity price drop significantly, which attracts users to dynamically adjust their own power consumption strategy (i.e., ESS charging, load demand increase).

To sum up, the local consumption of distributed energy can be achieved flexibly and the stability impact of the grid connection of distributed energy can be reduced by building a local trading market composed of DNO and regional microgrids. The electricity price is used to indirectly mobilize users to participate in dispatching of active distribution system by introducing market factors. This method effectively prevents the operation safety problems, such as blockage of grid lines during peak power consumption and low energy utilization during low peak power consumption.

5.2.2 Model validation analysis

In order to verify the accuracy of the second-order cone relaxation of the proposed model, the validation analysis of the model is carried out in this section (Li et al., 2017). Gap value of the whole system in each period is shown in Figure 8. It can be seen that the error values of the whole system are all at 10^{-4} . Therefore, the results calculated by the proposed method achieve acceptable accuracy.

5.2.3 Case studies

This section compares the proposed decision-making method with the other two models to prove its effectiveness. Specific cases are defined as follows.

Case I. Economy-oriented transactive control. In this case, only economy-concerned factors are considered, thus the power flow, line power losses and voltage deviation are not included (Liu et al., 2020).

Case II. Compared with Case III, this case does not consider the use of SOPs.

Case III. The proposed method in previous sections.

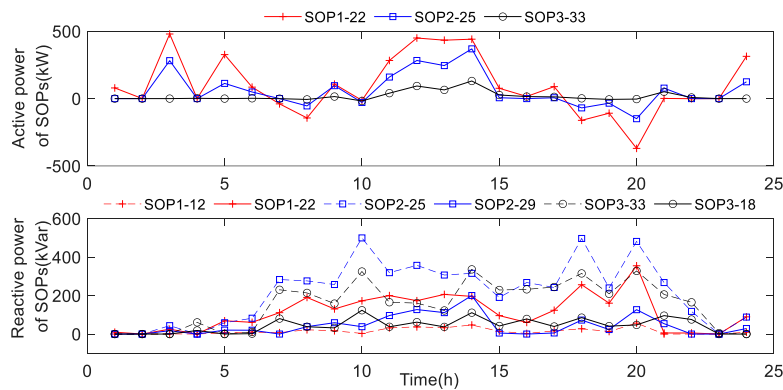


FIGURE 10
SOP active/reactive power control result.

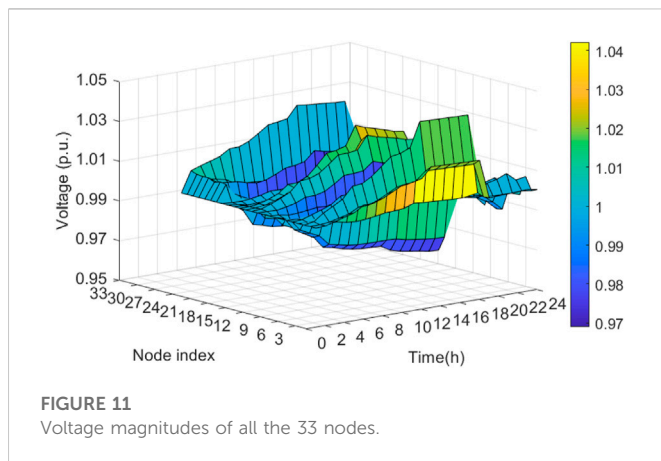


FIGURE 11
Voltage magnitudes of all the 33 nodes.

The comparison results of maximum and minimum voltage are shown in Figure 9, the comparison results of OLTC control are shown in Figure 12, and the comparison results of the relevant performances are shown in Table 3.

The active/reactive power control results of SOPs in Case III are shown in Figure 10. SOP1 is connected to microgrid one and microgrid 3, SOP2 is connected to microgrid one and microgrid 2, SOP3 is connected to microgrid two and microgrid 3. The voltage fluctuation is shown in Figure 11.

Table 3 shows that the energy storage system and demand response have been fully mobilized thanks to Case I does not need to consider the violation of network constraints, which reduces the cost of the microgrid. However, the results, which are compared with Case III, have greater line loss and voltage deviation. And Figure 10 shows that voltage violation is increased, which causes a big potential safety hazard to the operation of the actual active distribution system and affects whether the actual transaction can be completed smoothly and timely.

Compared with Case III, the line power losses and the cost in Case II increase to a greater extent. Figure 9 and Figure 11 show that SOP keeps the voltage amplitude strictly within the safe range (i.e., [0.96, 1.04] p.u.), which adjusts the system power to eliminate voltage violations and alleviates the problem of voltage rise. It proves the

advantages of SOP in solving the security problems of active distribution system. Figure 10 and Figures 4–7 show that active power control of the SOP is consistent with the action of energy storage systems and the transferable loads in each regional microgrid. This situation reflects that SOP can adjust the active power flow distribution of the system flexibly and rapidly. The problem of transaction delay or failure caused by route congestion can be avoided through the connection between SOP and DNO. Therefore, the power flow fluctuation caused by renewable energy can be eliminated rapidly, and the economy of the overall operation of the distribution network can be improved indirectly. Furthermore, Figure 12 shows that the OLTC has less switching actions. The economic cost of active distribution system can be effectively reduced through the cooperation of SOP and OLTC.

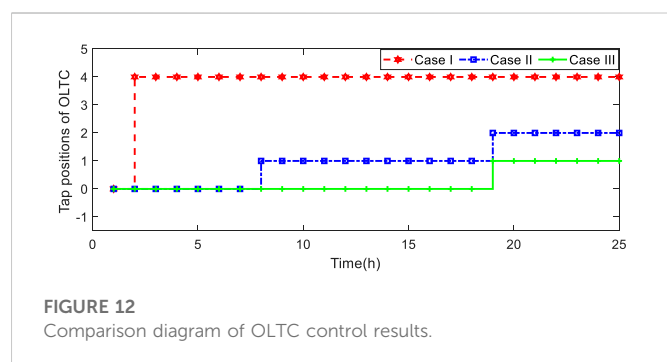
To sum up, it can be verified that the proposed comprehensive regulation method can give consideration to both operating economy and voltage security, and propose a more efficient scheme for consuming local distributed energy.

5.3 Convergence analysis of distributed robust optimization

In this section, the DRO solution is tested and analyzed. Table 4 shows that the deviation between the main problem and the subproblem in the algorithm reaches 10^{-3} levels of accuracy after three iterations. This shows that C&CG algorithm can quickly solve the distributed robust optimization model proposed in this paper.

5.4 Comparison of distributed robust optimization methods

This paper assumes that the prediction errors of PV, WT and DR follow the Normal Distribution which the mean is set to 0 and the variance is set to .4 times of the predicted value (Ding et al., 2018). 3000 error scenario data are generated by fitting to represent the historical data. Finally, five typical scenarios are selected for simulation analysis of distributed robust optimization methods.

**TABLE 4 Results of iterative convergence.**

Iterations	Upper bound	Lower bound
1	457.032	452.890
2	457.028	456.697
3	456.998	456.998

TABLE 5 The results of Comparison under different confidence intervals.

α_1	α_{∞}		
	.5	.8	.99
.2	454.001	455.213	456.945
.5	454.866	455.267	456.998
.8	454.891	455.433	456.998

5.4.1 Comparative analysis of results under different confidence intervals

In order to show the influence trend of different confidence on the optimization results, and to prove the effectiveness of the comprehensive norm compared with the single norm, the following comparative analysis is made.

First, the results of distributed robust optimization under different confidence intervals are compared when the comprehensive norm constraint is adopted. Here, the range of α_1 is [.2, .8], and the range of α_{∞} is [.5, .99]. The results are shown in Table 5.

It can be observed from Table 5 that the value of the total cost increases with the increase of the comprehensive norm confidence α_1 and α_{∞} . This situation shows that the increase of confidence interval will increase the uncertainty contained in the system. This also means that the distribution network system needs to optimize the transaction content and call more resources (such as SOP) to eliminate the adverse impact of uncertainty on the system operation. This is the reason why the total cost of the system increases.

The results of comprehensive norm and single norm-inf are compared. Here α_{∞} selects .99. The results are shown in Table 6.

It is shown that the results obtained by using the constraint condition of comprehensive norm are smaller than those obtained by using the norm-inf method. This means that comprehensive norm has better economy. Moreover, the comprehensive norm and single norm-1 results are compared. Here, α_1 is selected as .5. The results are shown in Table 7.

TABLE 6 Comparison of result between comprehensive norm and norm-inf.

α_1	Target value	
	Comprehensive norm	α_{∞}
.2	456.945	467.208
.5	456.998	467.208
.8	456.998	467.208

TABLE 7 Comparison of result between comprehensive norm-inf and norm-1.

α_{∞}	Target value	
	Comprehensive norm	α_1
.5	454.866	461.967
.8	455.267	461.967
.99	456.998	461.967

It can be observed from Table 7 that the calculated results of comprehensive norm are smaller thanks to the constraint of comprehensive norm further limits the fluctuation range of uncertainty. This also means that the overall cost of the system is lower and the conservatism of the results is improved.

According to the above conclusions, it can be proved that the comprehensive norm is more effective than the single norm.

5.4.2 Analysis and comparison of distributed robust optimization and other methods

This part will compare the stochastic optimization, robust optimization and the DRO adopted in this paper. Here, the stochastic optimization is calculated based on the scenarios known by the distributed robust method, where the probability values of each scenario are .2; The robust optimization uses .4 times of the predicted value as the fluctuation range; The comprehensive norm constraint of DRO that α_{∞} selects .99 and α_1 selects .8. The comparison results are shown in Table 8.

To prove the effectiveness of the distributed robust optimization method in this paper, 6000 random probability distribution combinations are randomly generated based on the prediction scenario, and three result schemes are implemented to obtain the mean value of the expected cost of the probability distribution. The results are shown in Table 9.

According to Table 8 and Table 9, although the optimization result of stochastic optimization based on known scenarios is the smallest, the result is always greater than that of distributed robust optimization when the randomness of scenarios is fully considered. This situation indicates that its robustness is obviously insufficient to that of distributed robust optimization. Because robust optimization only considers the worst scenario information, the result of network loss and cost is the largest.

Compared with the other two methods, the performance and cost of DRO are in the middle, and the expected mean value of the probability distribution cost is lower than the other two methods. This shows that its probability distribution average performance is better than the other two methods, which reflects its good balance

TABLE 8 Comparison of result between DRO and other methods.

System performance	Stochastic optimization	DRO	Robust optimization
Line power losses (kWh)	772.726	784.708	1320.350
SOP power losses (kWh)	477.643	478.863	878.427
Voltage deviation (p.u.)	16.341	16.531	20.538
Target value of DNO	413.725	456.998	1631.778
Total cost of MGs (¥)	2124.080	2158.872	2948.751

TABLE 9 Comparison of results of different algorithms.

α	Mean value		
	DRO	Stochastic optimization	Robust optimization
.2	397.414	487.366	525.312
.5	421.793	487.366	525.312
.8	445.929	487.366	525.312

in economy, conservatism and security and have better adaptability under the actual uncertainty environment.

6 Conclusion

In this paper, a distributionally robust transactive control method for active distribution systems with SOP-connected MMGs is proposed. First of all, the constructed local energy interactive market fully considers the system operation safety factors such as voltage quality, so that it can operate more safely, while ensuring the overall economy and the flexibility and autonomy of users. Secondly, SOP is introduced into the active distribution systems based on the local energy market, and associate it with DNO. This significantly reduces the line loss and voltage deviation, maintains the economic interests of each subject, and further improves the flexibility of internal transactions of active distribution systems. Then, KKT conditions, relaxation techniques and other techniques are used to transform the two-layer game problem into a single-layer MISOCP problem. The optimization of the complex coupling model is achieved, and the efficiency of the operation is improved. Thirdly, the modified DRO optimization method is combined with the active distribution system. Compared with the traditional stochastic and robust methods, the DRO method achieves a better balance in terms of economy and conservatism, and has better economy and uncertainty adaptability. Finally, the conservative strategy of the integrated regulation method can be flexibly adjusted by changing the confidence level of the ambiguity set. This situation shows that the decision-making level can reasonably choose between the operation economic cost and the operation safety risk according to the actual situation.

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Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YH: Conceptualization, investigation, methodology, software, validation, writing—Original draft, writing—review and editing; YXi: Conceptualization, methodology, data curation; ZY: Supervision, project administration; YX: Supervision, project administration; GW: Supervision, project administration; LJ: Validation.

Funding

The authors gratefully acknowledge the support of the National Natural Science Foundation of China (52007074, U22B20116).

Conflict of interest

YZ was employed by Economic and Technological Research Institute of State Grid Anhui Electric Power Co., Ltd. and GW was employed by State Grid Anhui Electric Power Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Glossary

N_T Total number of time periods.

N_N Total number of nodes.

N_{mg} Total number of microgrids (MGs) inside the distribution network (DN).

Ω_l Set of all the branches.

Ω_o Set of all the branches with on-load tap changer (OLTC).

S_n Node set of MG n .

N_e Total number of energy storage system (ESS) inside the MG.

N_ω Total number of discrete scenarios.

ω Index of scenarios.

ψ Feasible region of p_ω .

γ_t^b/γ_t^s Trading prices with HV grid.

g_t Net load of DN system.

C_{loss}/C_{OLTC} Cost coefficients associated with power losses and OLTC, respectively.

r_{ij} Resistance of branch ij .

$I_{t,ij}$ Current of branch ij at period t .

Δt Discrete time interval

$\tilde{U}_{ref}$ Reference voltage point.

$P_{t,i}^{PV}/Q_{t,i}^{PV}$ Active/reactive power injected by PV array at node i at period t .

θ_k^{PV} Power factor angle of PV k .

S_i^{PV} Capacity of PV i .

$P_{t,i}^{Wind}/Q_{t,i}^{Wind}$ Active/reactive power injected by wind turbine at node i at period t .

$P_{t,i}^{L,unc}$ General load at node i at period t

$\bar{I}$ Upper current limit.

$\bar{U}/U$ Upper/lower limits of statutory voltage range.

S_i^{SOP} Capacity of VSC at node i .

$Q_i^{SOP}/\bar{Q}_i^{SOP}$ Reactive power boundaries of VSC at node i .

$\lambda_t^{\min}/\lambda_t^{\max}$ Upper and lower bounds of the internal transaction price at period t .

C_{deg} Coefficients concerning ESS degradation.

$\eta^{ess,c}/\eta^{ess,d}$ Power exchange efficiencies of the ESS.

$S_e^{\min}/S_e^{\max}$ SoC boundaries of ESS e .

μ/λ Dual variables of inequality/equality constraints in optimization model of MGs.

p_ω Probability of scenario ω .

δ_1/δ_∞ Tolerant limit of norm-1/norm-inf of the ambiguity set in the distributed robust optimization (DRO) model.

p vector of element p_ω .

m Number of iterations.

M Infinite positive integer

$P_{t,i}^{sop,loss}$ Active power losses caused by SOP at period t .

λ_t Clearing price of the energy trading market at period t .

$P_{t,n}^{net}$ Net load of MG n at period t .

$P_{t,i}/Q_{t,i}$ Sum of active/reactive power injection at node i at period t .

$P_{t,ij}/Q_{t,ij}$ Active/reactive power flow of branch ij at period t .

$U_{t,i}$ Voltage magnitude of node i at period t .

$P_{t,i}^L/Q_{t,i}^L$ Active/reactive load consumptions of node i at period t .

$c_{t,i}^{ess}/d_{t,i}^{ess}$ Charging/discharging power of ESS i at period t .

$P_{t,i}^{SOP}/Q_{t,i}^{SOP}$ Active/reactive power injection by VSC at node i at period t .

$P_{t,i}^{L,up}/P_{t,i}^{L,down}$ Increased/decreased load demands due to the demand response (DR) program.

$P_{t,i}^{ess,c}/P_{t,i}^{ess,d}$ Charging/discharging power of ESS.

p_ω^+/p_ω^- Positive/negative probability value offset of p_ω .

$K_{t,ij}$ Number of the tap steps and turns ratio of the OLTC connected to branch ij at period t .



OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process and Energy Systems Engineering, a section of the journal Frontiers in Energy Research

RECEIVED 07 November 2022

ACCEPTED 22 November 2022

PUBLISHED 19 January 2023

CITATION

Hu X, Meng L and Su C (2023), The coordinated operation strategy of multi-type power generations in different modes in prosumer with high renewables.
Front. Energy Res. 10:1091574.
doi: 10.3389/fenrg.2022.1091574

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The coordinated operation strategy of multi-type power generations in different modes in prosumer with high renewables

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The renewable energy with distributed generation is widely used because of the cleanliness and sustainability. However, when high renewables connect to the grid, the randomness and intermittent of the renewable energy will deteriorate the performance. As the important interface between distributed generations and power grid, the prosumer can contribute to the improvement of the renewable energy penetration if stable and reliable operation of the power supply is realized. The prosumer has multi-type generations, loads and auxiliary converters, where the characteristics interact each other. Moreover, due to the complicated grid states, the prosumer may operate in different conditions. Therefore, the research on the coordinated operation control strategy of the multiple electrical facilities is necessary in the prosumer with high renewables. In this paper, the AC/DC hybrid prosumer is established with multi-type distributed generations, loads and auxiliary converters. The prosumer can operate in normal grid-connected mode and grid-fluctuation mode. In different modes, the cooperation control of the power converter in the prosumer is proposed, which changes according to the grid demands. When over-limited grid voltage and frequency fluctuation are detected in the point of common coupling, the prosumer can switch from normal grid-connected mode to grid-fluctuation mode to provide voltage and frequency support. Finally, the simulation results based on Matlab/Simulink is employed to verify the effectiveness of the proposed control strategy.

KEYWORDS

prosumer, renewable energy, distributed generation, virtual synchronous generator, coordinated operation strategy, mode-switching control

1 Introduction

Due to the rapid depletion of fossil fuels and increasingly serious environmental problems, renewable energy sources (RES) have developed quickly (Bollen et al., 2005). Meanwhile, to manage the energy more effectively and flexibly, the renewable energy resources can use distributed generation (DG) to generate electricity, including the renewables, the energy storage (ES) and the micro-turbine for multi-source complementary (Cady et al., 2015; Elavarasan et al., 2020). The DG correlates with the

customer demand and other auxiliary converters to form the prosumer. The prosumer needs the management of the generation, the consumption, and the auxiliary converters to effectively utilize the renewables and ensure the stable grid connection (Liu et al., 2020; Zhu et al., 2020). In the recent future, the prosumer may be one of the main forms of the distribution networks.

Currently, the intermittence and fluctuation of renewable energy sources in both the power grid and the prosumer may cause serious problems, including the power unbalance and voltage fluctuation (Yin et al., 2017; Li et al., 2018). Therefore, when the prosumer connects to the power grid, the management is important in dealing with disturbance inside and outside the prosumer. Because the disturbance is from many different reasons, the DGs and auxiliary converters in prosumer should use different operation strategies according to the characteristics of themselves to provide different service for the grid.

For the photovoltaic (PV) generation, the traditional maximum power point tracking (MPPT) control cannot support the voltage and frequency in ac-bus in the prosumer when it is disturbed (Wang et al., 2022). If the voltage and frequency cannot meet the power quality requirement, the prosumer will shut down to avoid deteriorating the ac-bus. At present, the maximum power point quitting (MPPQ) control can be used to reserve a certain PV output margin to provide corresponding support to the grid when the grid or RES fluctuates (Ropp et al., 2016; Wang et al., 2019). This is a rational compromise between economic efficiency of the renewables and the power quality of the grid. Moreover, energy storage is another important component of the prosumer with highly flexible and controllable power, as well as the fast response speed. ES can play a role of peak shaving and valley filling to meet load demand when connects to the grid and can provide uninterrupted power supply for local loads when disconnected with the grid (Boicea et al., 2014) (Ortega et al., 2016). When the prosumer connects to the grid, the stable connection and high utilization of renewable energy is most important. Inevitable voltage and frequency fluctuation is usually observed (Zhou et al., 2019). The prosumer needs to decrease the fluctuation caused by the renewables and varying loads to reduce the negative impact on the power grid (He et al., 2015). In this situation, more types of DGs in the prosumer should change their control strategy and provide ancillary service for the grid to participate in the frequency modulation and peak regulation.

What's more, when encountering disturbances, prosumers can switch from normal grid-connected mode to grid-fluctuation mode in the extreme case. To solve this problem, other auxiliary converters for interlinking the DC and AC network and power improvement should work with different control strategies in the regulation of the prosumer (Buraimoh and Davidson, 2021). Then, the mode switch of the DGs in the prosumer is needed, which increases the difficulty for the coordinated operation of the prosumer (Liu et al., 2022). Therefore, the research on the

coordinated operation control strategy of the converters in different modes is necessary. The management of multiple energy sources, multi-type loads and auxiliary converters is essential in the prosumer, where the facilities need different control modes according to the demand and respective characteristics (Teng et al., 2019; Zhang et al., 2019). In the meantime, the regulable facilities in the prosumer are also increased. Thus, the research on the coordinated operation control of the prosumer with multiple electrical converters in different situation is indispensable.

The energy resources and local loads are multifarious in the prosumer, and most of them connect to the prosumer by power converters, which has the advantages in realizing complex dynamic characteristic (Tian et al., 2020). At present, research on the control strategies of DG to support grid control has caused widespread concern. For renewable energy generations, the sampling converter method is adopted to provide the maximum power point information for other power generations to regulate the RES (Rizwin et al., 2020). The voltage control and current control strategy can be adopted to provide voltage and frequency support for the system, like droop control and virtual synchronous generator (VSG) control (Meng et al., 2019; Liu et al., 2022). In the literatures (Jia et al., 2016) and (Xu et al., 2022), droop control strategy of PV inverters is proposed to provide voltage and frequency support for the power grid. In the meantime, to improve the dynamic performance, the VSG control strategy is employed in the DGs to emulate the synchronous generator's (SG's) electromechanical transient characteristics (D'Arco et al., 2014; Yuan et al., 2016; Li et al., 2018). Furthermore, the research on the control strategies for multi-inverters in parallel is also applicable in the prosumer. For the prosumer with several photovoltaic inverters, the sample PV inverter can be employed to provide maximum power point information for other inverters to keep reserve capacity and high utilization (Xie et al., 2014; Hayde et al., 2017). In the literature (Shen et al., 2021), both of the voltage-controlled battery-storage inverter and current-controlled photovoltaic inverter adopt VSG control strategy and can operate in grid-connected mode. Nevertheless, present research usually focuses on the prosumer with two or three DGs and the research on the coordinated control strategy of the prosumer with high renewables and multi-type power generations is limited. For example, in the literatures (Hou et al., 2015; Mortezaei et al., 2015), the prosumer with multiple photovoltaic inverters is established to realize coordinated operation of high renewables and provide voltage and frequency support for the grid while the types of power supply in the prosumer are still not satisfactory. In the literatures (Qiu et al., 2022) and (Capuder et al., 2020), they establish the prosumer with multi-type power generations and the DGs can operate in parallel stably only in normal grid-connected mode. Therefore, the research on the coordinated operation

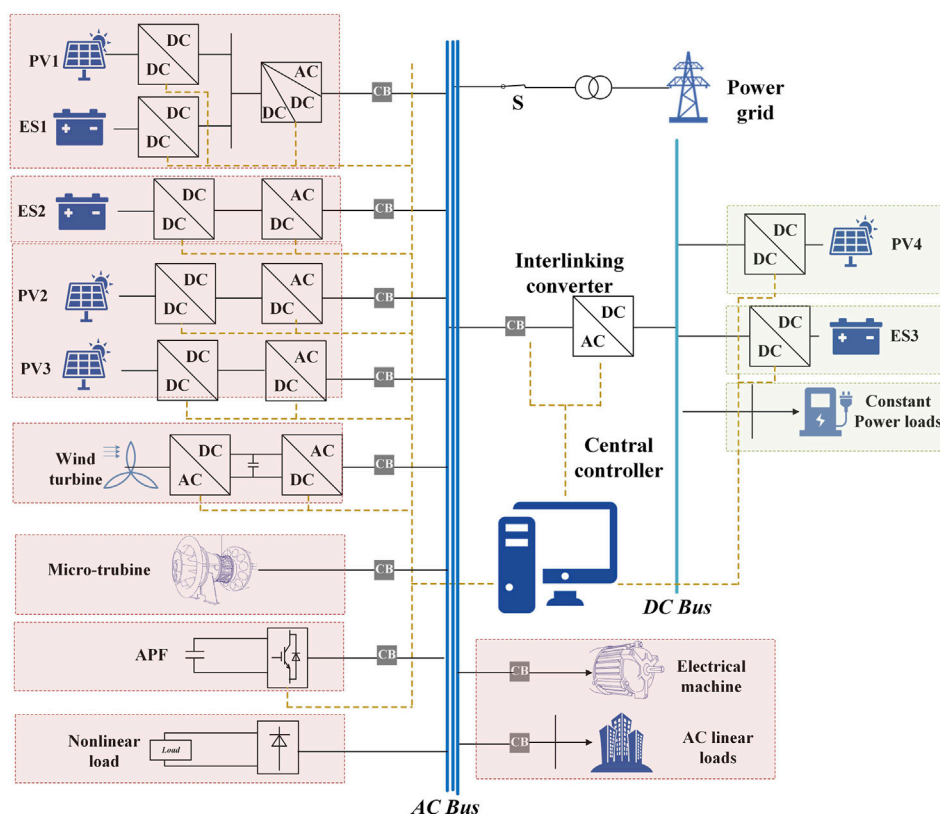


FIGURE 1
The prosumer's structure.

strategy of the prosumer's multiple generations in different modes still needs further study.

In this paper, the AC/DC hybrid microgrid with high renewables and various energy sources is built. The prosumer can stably operate in different modes, including normal grid-connected mode and grid-fluctuation mode. In normal grid-connected mode, the prosumer will be connected to the power grid. When large voltage and frequency deviation occur in the PCC, the prosumer will operate in grid-fluctuation mode, where more converter-interfaced facilities will provide ancillary service to participate in the voltage regulation. The coordinated control strategy of multiple power converters in the above modes is proposed with necessary operation mode switch. With the proposed method, the prosumer can actively participate in the active support of the grid in multiple situations.

2 The prosumer's structure with high renewables

The prosumer discussed in this paper includes both AC and DC bus, and this AC/DC hybrid structure is shown in the

Figure 1. To deal with different situations brought by the grid state change and RES power fluctuation, the prosumer needs to stably operate in different modes and provide proper ancillary function for the grid. The detailed description of this prosumer system is introduced in this section.

2.1 Systematic introduction of prosumer

When the prosumer with high renewables connects to the grid, the operation methods should be dependent on the states of renewable energy sources. What's more, because of the variations of the load power, the voltage in both the DC and AC bus will fluctuate as well. Therefore, the control target is to ensure the stable connection and reduce the impact caused by the renewable energy sources. Therefore, the prosumer should provide voltage and frequency support for the grid and effectively utilize the renewables in the meantime.

The prosumer with high renewables comprising of various energy resources is established. It includes both the AC part and DC part with different types of power supply and load.

The DC and AC part is connected to each other with an interlinking converter to balance the power between DC and AC bus. The load in the prosumer is designed multifarious. In the DC part, the constant power load is connected to the dc-bus by the buck converter. The AC system comprises of multi-type power supplies and local loads, including linear load, nonlinear load and electrical machine. Moreover, to enhance the power quality, the auxiliary electrical equipment for power quality improvement is considered. With all of these facilitates, the prosumer established in this paper includes the power supply, load, and auxiliary power converters, which can provide constructive information for the practical system with multi-type power generations with the multiple DGs and loads.

2.2 Multi-type facilities in the prosumer

The prosumer is powered by multiple energy sources. The DC-side subsystem includes a PV generation and a battery-storage generation, which are both connected to the dc-bus by the boost converter. The battery-storage system is used to reduce the fluctuation caused by the fluctuated PV power. The two distributed generations supply power for the constant power loads. In the AC system, the renewable energy sources comprise of the wind power and solar energy. The wind power is feeding to the ac-bus by a back-to-back converter. At the same time, the integrated renewable energy and storage system is connected to the prosumer by the two-stage inverter, which includes two kinds of methods. On the one hand, the only PV panels are connected to the ac-bus only by the two-stage inverter, including the PV2 and PV3. On the other hand, the photovoltaic generation PV1 and the battery-storage ES1 are connected to the DC side of the inverter by the boost converters, which is a two-stage topology. A battery-storage generation ES2 supplies power to the prosumer by the two-stage inverters. Besides, the DGs in the AC part also include the gas turbine with the SG. All the generations mentioned above operate in parallel and constitute the prosumer's power supply system. The local loads in the AC side consist of linear loads, nonlinear loads and electrical machine. In addition, some auxiliary converters provide the functional management in the prosumer, which includes the active power filter and the interlinking converter.

The prosumer is considered to operate at normal grid-connected mode and grid-fluctuation mode. Considering that the prosumer should deal with different possible situations, the facilitates in prosumer should operates in different modes. As power converters are widely used in the prosumer, he facilities with converter are controlled to flexibly operate in different modes to support the requirement, and hence, the prosumer can provide the AC-bus voltage support and supply power to the loads independently.

3 Control modes of generations in prosumer

The structure and targets of the prosumer are introduced in the last chapter. To realize stable operation and grid support, the coordinate control of the generations is necessary. Before that, in this chapter, the control strategies of the DG, load, and auxiliary converters with different operation modes are introduced.

3.1 RES-integrated converter

As introduced in the chapter 2, the renewable energy sources are deployed in both DC part and AC part of the prosumer including wind turbine and PV panels. The wind turbine is connected to the ac-bus by the back-to-back converter with the asynchronous machine. The grid-side converter is employed to stabilize the DC link voltage and realize unity power factor operation, while the generator-side converter is used for the control of the output active power and the output voltage. In the DC part, the PV panel is connected to the dc-bus by the boost converter, while the PV generations in AC part are connected to the prosumer by the inverters as shown in the [Figures 2, 3](#). The control strategies of the PV converters are discussed in detail in this section.

3.1.1 Maximum power point tracking control

The relationship between the output voltage and output power of PV cell is nonlinear with a maximum power point according to the photovoltaic characteristics that will change with the temperature and the illumination. Therefore, the P&O MPPT control strategy is realized in the boost converter ([Hamidon et al., 2012](#)). The detailed implementation of the control loop is illustrated in the [Figure 2](#). The PV inverter adopts current control to stabilize the voltage on the inverter's DC side, and the control diagram is shown in the [Figure 2](#). The voltage on the inverter's DC side will follow up the command value U_{dc_ref} . In this control mode, the PV inverter is synchronized with the grid by a phase-locked loop (PLL) and is employed as the current source in the prosumer, which is also a grid-following control method.

3.1.2 Constant active and reactive power tracking control

When the PV inverter adopts MPPT control strategy, the energy utilization is the most effective. However, this method has the weakness in power adjustment, power reserve and power curtailment. When the power fluctuation occurs in the grid, the PV inverter can't adjust its output power to support the system. Hence, the constant active and reactive power tracking (CPQT) is used as one of the control modes to solve this problem ([Liu et al., 2015](#)). The PV inverter adopting CPQT control strategy usually operates under its maximum power point and can change its

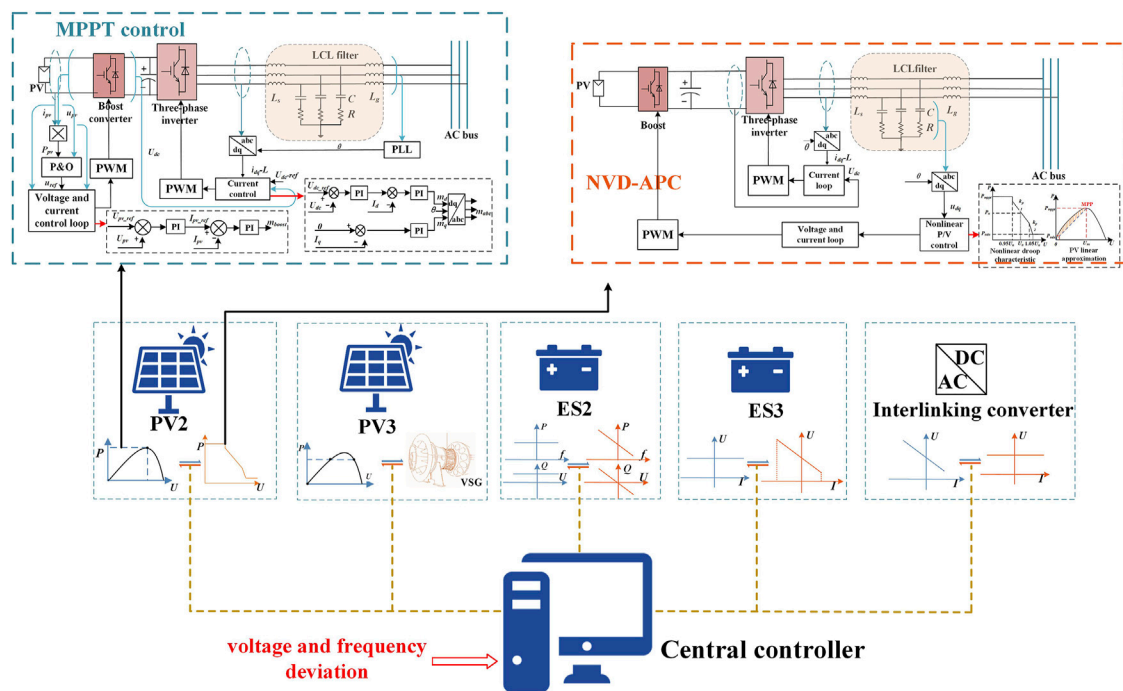


FIGURE 2
The control diagram of PV2.

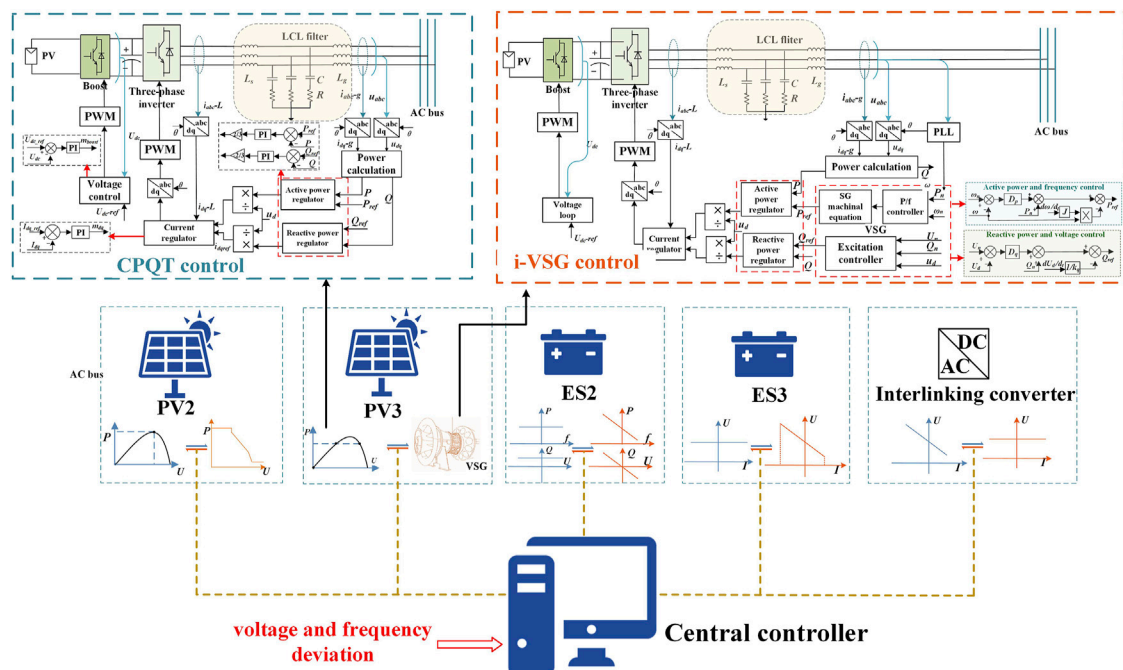


FIGURE 3
The control diagram of PV3.

output power according to the instruction from the central controller. The detailed control method is as follows.

The PV inverter in CPQT control mode stabilizes the voltage on the inverter's DC side by the boost converter and the control target is realized by the single voltage control loop as shown in the Figure 3. Firstly, the output voltage and current in the PCC U_{abc} and I_{abc-g} should be transferred from abc coordinates to dq coordinates to calculate the output power based on the frequency information of U_{abc} from the PLL. The power-calculating formula is shown below.

$$\begin{cases} P = \frac{3}{2} (U_d I_{gd} + U_q I_{gq}) \\ Q = \frac{3}{2} (U_q I_{gd} - U_d I_{gq}) \end{cases} \quad (1)$$

where P is the output active power, Q is the output reactive power, U_d is the d-axis voltage, U_q is the q-axis voltage, I_d is the d-axis current, I_q is the q-axis current. Then the inverter adopts power and current control loop to realize the CPQT control. The control loop is shown in the Figure 3. In the external power loop, the difference between the reference value and the actual output power is given to the proportional integral (PI) controllers, whose results is used for the calculation of the reference value of the inverter's output current based on the power-calculating formula. Then the inner loops will realize current command tracking by PI controllers.

3.1.3 Nonlinear-voltage-droop active power control

Droop control is usually used as a kind of voltage control method when grid support is needed. In traditional droop control methods, voltage support is provided based on the active and reactive power regulation. However, these methods usually neglect the ability in active power control in RES-based converter's control. To solve the problem, the droop control in PV converter is proposed, where a new nonlinear droop based active power control (NVD-APC) method is proposed to further improve the performance. The PV output power is limited by the MPP, and the solar energy might be wasted adopting linear control method. Meanwhile, the constant droop coefficient will lead to the poor voltage-supporting performance when the voltage deviation is too large. Therefore, the NVD-APC method changes the output active power according to the voltage deviation based on the nonlinear P/V droop characteristic shown in the Figure 2. In the nonlinear droop control mode, the output of the PV inverter decreases with the increase of the voltage in AC bus. When the voltage is much higher than the nominal value, the droop coefficient will be increased to accelerate the power reduction. On the contrary, when the voltage is too low, the PV inverter will operate at the maximum power point. The control method is illustrated in the Figure 2. The nonlinear droop control is realized in the boost converter. Firstly, the voltage deviation will be used for the

calculation of the reference value of the inverter's output active power based on the nonlinear P/V droop characteristic. The relationship can be described by the Eq. 2.

$$\begin{cases} P_{ref} = P_{mptt} & U_d < 0.95U_n \\ P_{ref} = P_n + k_{p1}(U_n - U_d) & 1.05U_n > U_d > 0.95U_n \\ P_{ref} = P_n + k_{p2}(U_n - U_d) & U_d > 1.05U_n \end{cases} \quad (2)$$

where P_{ref} is the reference value of the PV inverter's output active power, P_{mptt} is the maximum power of the PV cell, U_d is the amplitude of the PCC voltage, U_n is the rated voltage, P_n is the inverter's rated output active power, k_{p1} and k_{p2} are the droop coefficient. Especially, $k_{p2} > k_{p1} > 0$.

Then based on the maximum power point from a pre-set sampling battery, the linear approximated curve of the PV characteristics is used to calculate the reference value of the PV cell's output voltage (shown in the Figure 2). The boost converter realizes the output power control by regulating the PV output directly and the equation is shown in Eq. 3. Moreover, the minimum output power P_{min} depends on the minimum PV output voltage decided by the maximum transformation ratio of the boost converter.

$$U_{ref} = k_{pv} \cdot P_{ref} = \frac{U_m}{P_{mptt}} \cdot P_{ref} \quad (3)$$

where U_{ref} is the reference value of the PV output voltage, P_{ref} is the reference value of the PV output power, k_{pv} is coefficient of the linear approximated curve of the PV characteristics, P_{mptt} is the maximum power of the PV cell, U_m is the PV output voltage at maximum power point.

With the information of U_{ref} the boost converter adopts voltage and current control loops to realize voltage tracking as shown in the Figure 2. The inverter's control method is the same as that in MPPT control.

3.1.4 I-VSG control mode

The inverters adopting current-controlled VSG (i-VSG) control strategy are regarded as the current source, which synchronize with the grid by PLLs. In this control mode, the VSG control emulates the SG's primary voltage and frequency regulation characteristics by adding droop characteristics and virtual inertia to the control loop (Fan et al., 2021). The output of the SG emulation control part in i-VSG is the reference value of the output power and the central control equations are shown in Eqs 4, 5 with the illustration in the Figure 3.

$$Q_{ref} = Q_n + D_q (U_n - U_d) - \frac{dU_d}{k_q dt} \quad (4)$$

$$P_{ref} = P_n + D_p (\omega_n - \omega) - J\omega \frac{d\omega}{dt} \quad (5)$$

where Q_{ref} and P_{ref} are the reference value of the inverter's output reactive power and active power respectively, Q_n and P_n are the nominal power of the inverter, U_n is the inverter's nominal output voltage, ω_n is the inverter's nominal angular frequency,

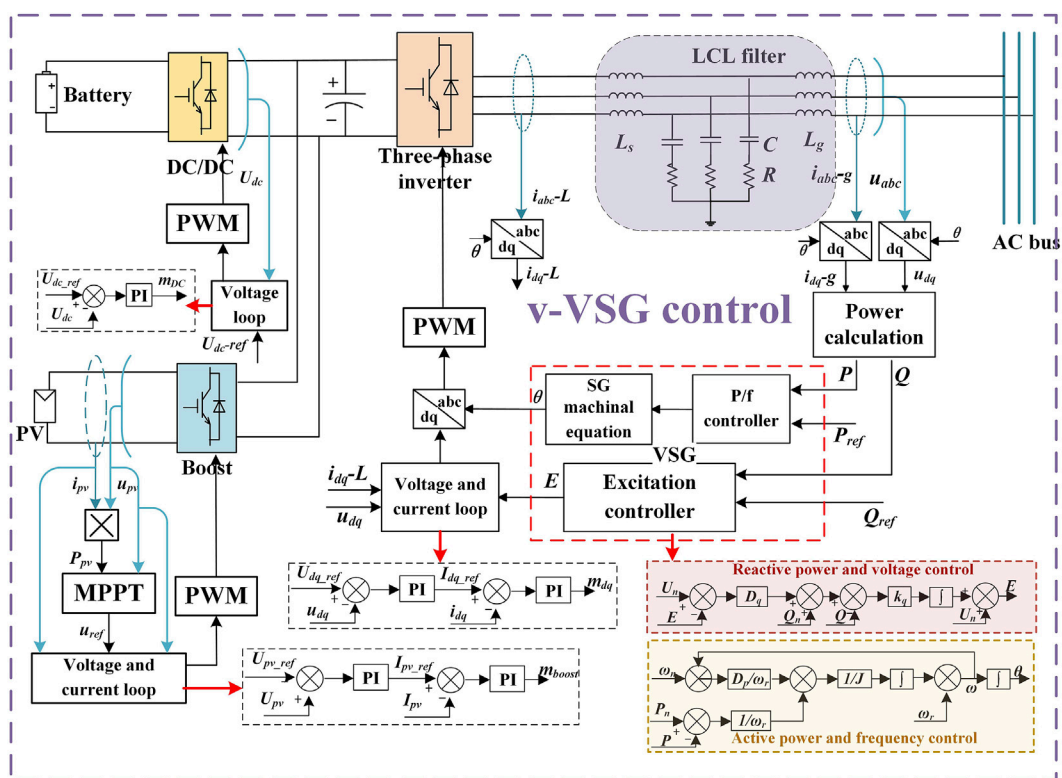


FIGURE 4
The control diagram of the integrated inverter.

U_d is the inverter's output voltage, ω is the inverter's angular frequency derived from the PLL, J is the virtual inertia.

Therefore, based on the calculation results of the output power reference, the inverter in i-VSG control mode can realize power command tracking with a similar power and current control loop used in the CPQT control (shown in the Figure 3). At the same time, the boost converter's control strategy is the same as that in CPQT control. Compared to NVD-APC method, the PV generation adopting i-VSG control can provide voltage and frequency support by emulating the SG's characteristics, where the power adjustment is realized in the inverter. What's more, in this control modes the virtual inertia is introduced to improve the frequency dynamics of the system.

3.2 Integrated renewables and storage inverter

The integrated renewables and storage inverter consist of the PV source and the battery-storage, whose main circuit is shown in the Figure 4. The PV cell and the battery are connected by two separated DC/DC converters, where the boost converter adopts MPPT control strategy. Then the

reference value U_{pv_ref} will be incorporated into the voltage and current loop shown in the Figure 4 to change the PV output power. The battery adopts the single voltage control loop to keep the stable voltage on the inverter's DC side. When the maximum power of PV cell is larger than the output power of the inverter, the battery will absorb the surplus power with the bi-directional power conversion. On the contrary, when the power can't meet the inverter's power reference, the battery will supply power to the system. The inverter shown in the Figure 4 adopts voltage-controlled VSG (v-VSG) control strategy (Wang et al., 2021). The control diagram is also illustrated in the Figure 4. The inverter emulates the SG's characteristics based on the Eqs 4, 5 introduced in the Section 3.1.4. The reactive power and voltage control equation is shown below.

$$Q_n - Q - D_q(E - U_n) = \frac{dE}{k_q dt} \quad (6)$$

where Q_n is the nominal reactive power of the inverter, Q is the inverter's output reactive power, U_n is the nominal voltage of the inverter, E is the reference value of the inverter's output voltage, D_q is the droop coefficient of the reactive power and voltage control loop, k_q is the integral coefficient of the reactive power and voltage control loop.

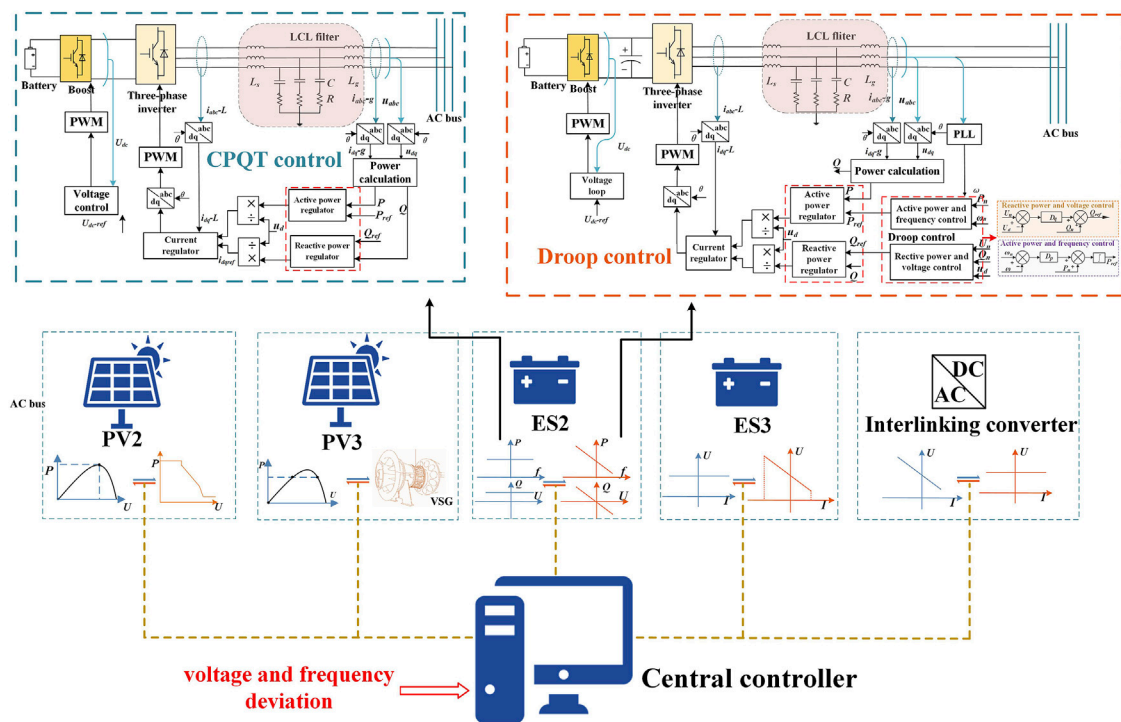


FIGURE 5
The control diagram of ES2.

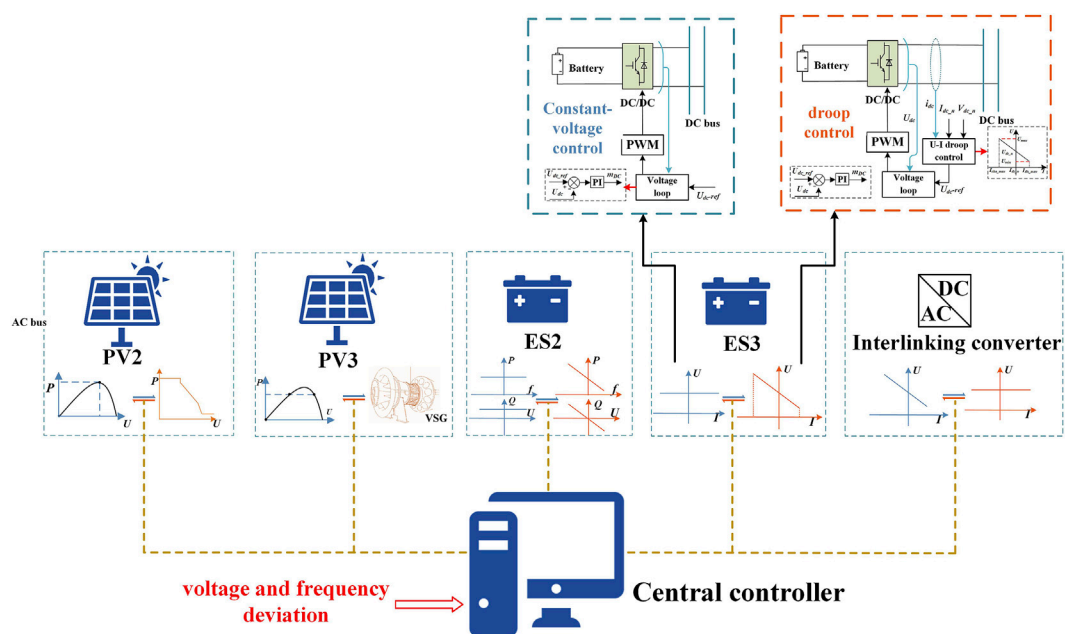


FIGURE 6
The control diagram of ES3.

At the same time, compared to the droop control, the active power and frequency control in VSG control introduces virtual inertia for the improvement of the frequency dynamics in the Figure 4. The governing equation is as the below equation.

$$P_n - P - D_p(\omega - \omega_n) = J\omega \frac{d\omega}{dt} \quad (7)$$

where P_n is the nominal active power of the inverter, P is the inverter's output active power, ω_n is the nominal angular frequency of the inverter, ω is the inverter's angular frequency, D_p is the droop coefficient of the active power and frequency control loop, J is the virtual inertia. Based on the voltage and frequency information calculated in the above two equations, the inverter adopts the voltage and current control loop to control the output voltage.

3.3 Battery-storage converter

In the prosumer, the battery storage is applied in both the DC part and AC part as shown in the Figures 5, 6. In the DC part, the battery is connected to the dc-bus by the bi-directional DC/DC converter, which works in the droop control mode and constant-voltage mode. The control modes of battery-storage inverter include PQ control and droop control, while the control strategy of PQ control mode is same as the method introduced in the Section 3.1.2. The control diagram of ES2 is shown in the Figure 5.

3.3.1 Droop control in DC part

The droop control can be used for the limitation of the voltage deviation in dc-bus caused by the fluctuation of the PV output power. There is a droop relationship between the dc-bus voltage and the ES's output power which can be expressed by the Eq. 8.

$$P_{ES} = P_0 + \frac{U_0 - U_{dc}}{\beta} \quad (8)$$

where P_{ES} is the output of battery-storage converter, U_{dc} is the dc-bus voltage, U_0 is the rated value of dc-bus voltage, P_0 is the rated output power, β is the power and voltage droop coefficient. Meanwhile, the relationship between the output current and the power can be written below.

$$I_{ES} = \frac{P_{ES}}{U_{dc}} \quad (9)$$

where I_{ES} is the battery-storage converter's output current. Hence, by simplifying the above two equations, the voltage and current droop characteristic can be written as the following equation, where k is the voltage and current droop coefficient and I_0 is the ES's rated output current. The droop relationship is illustrated in the Figure 6.

$$I_{ES} = \frac{P_0}{U_{dc}} + \frac{U_0 - U_{dc}}{\beta U_{dc}} \approx \frac{P_0}{U_{dc_{ref}}} + \frac{U_0 - U_{dc}}{\beta U_{dc_{ref}}} = I_0 + k(U_0 - U_{dc}) \quad (10)$$

When the voltage U_{dc} is too high and the PV output power is surplus, the charging current of the battery-storage will be increased to lower the voltage. Conversely, when the output power can't meet the demand and the voltage is lower than the rated value, the battery-storage converter will increase the discharging current. The droop control is realized by the voltage and current control loop shown in Figure 6, where the reference output voltage is calculated based on the droop characteristic.

3.3.2 Droop control in AC part

The droop control strategy of battery-storage inverter is shown in the Figure 5, which is also a two-stage inverter. The boost converter is still used for the DC voltage support and droop control is realized in the three-phase inverter. The control principle of droop control is the i-VSG control, which calculates the active power and reactive power reference value based on the relationship between the output power and voltage vector. The droop characteristics can be written as Eq. 11.

$$\begin{cases} Q_{ref} = Q_n - D_q(U_d - U_n) \\ P_{ref} = P_n - D_p(\omega - \omega_n) \end{cases} \quad (11)$$

where Q_n and P_n are the rated value of the inverter's output reactive power and active power respectively, Q_{ref} and P_{ref} are the output power of the inverter, U_n is the inverter's rated output voltage, ω_n is the inverter's rated angular frequency, U_d is the inverter's output voltage amplitude, ω is the inverter's angular frequency.

Based on the active power and reactive power reference value calculated by the droop characteristics, the inverter will realize the output power control by the power and current control loop which is shown in the Figure 5. The battery-storage inverter will regulate its output power when there is fluctuation in the system. When the prosumer works in normal grid-connected mode, the inverter will supply its rated power, while its output voltage is decided by the voltage in PCC. Moreover, the inverter will increase its output active power with the frequency reduction in PCC. And when the voltage in PCC is lower than the rated value, the output reactive power will be increased to support the voltage.

3.4 Micro-turbine

The micro-turbine is introduced in the prosumer as the distributed generator for other energy, which has the advantage in the improvement of the stability and dynamic performance. The micro-turbine in this paper consists of the gas turbine, synchronous generator and control system and

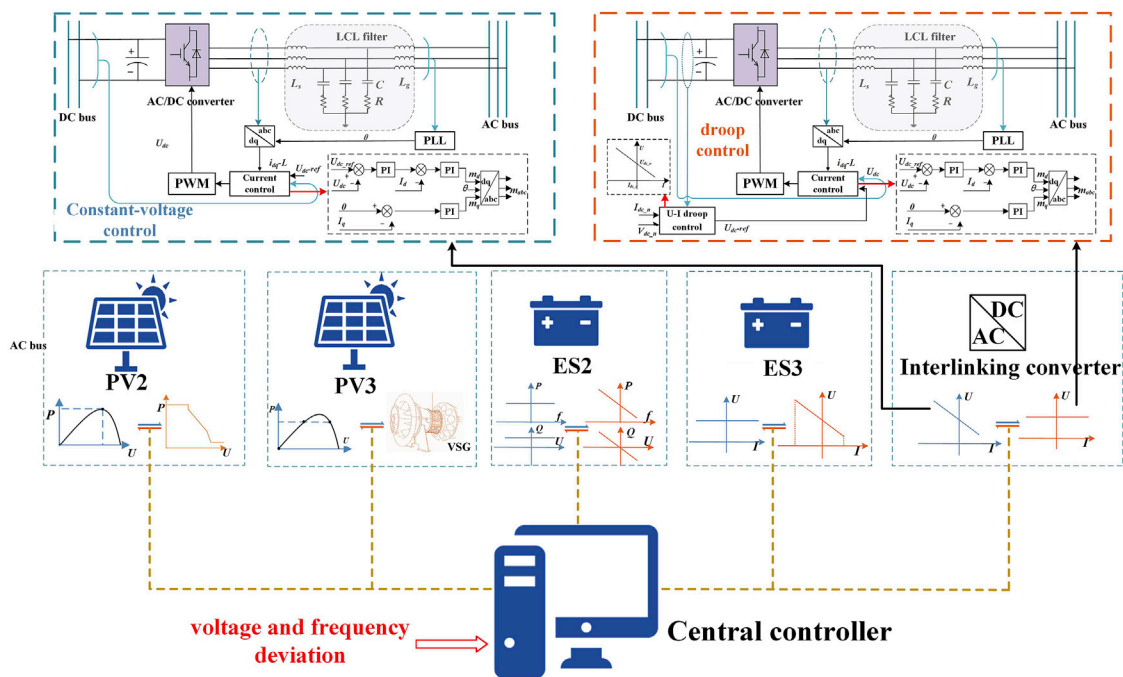


FIGURE 7
The control diagram of the interlinking converter.

operates in the constant power and voltage control (CPVC) mode to keep the output voltage and power stable. The control system includes speed control, mechanical torque control and acceleration control. The speed control is used to keep the SG's rotating speed stable which is realized by the speed control loop and fuel control loop. At the same time, the mechanical torque control is used to meet the power demand of the SG. Besides, the acceleration control is introduced to avoid too large thermal impact during drastic changes by adding acceleration feedforward control in the fuel control loop. Meanwhile, the control of excitation system is to regulate the excitation voltage to keep the amplitude of stator voltage stable.

3.5 Auxiliary power converters

In the prosumer, beside of the converters employed in the DGs, the auxiliary converters, including interlinking converter and active power filter, also provide necessary service to support the grid.

3.5.1 Interlinking converter

The interlinking converter in the prosumer is one bi-directional DC/AC converter used for the connection of the DC part and AC part can operate in two modes. The converter

will work in rectifier operation mode when the output power of the PV generation and battery-storage generation can't meet the demand of the loads. By contrary, the converter will transfer the extra power to the AC part as an inverter. The control modes of the DC/AC converter are similar to the ES in DC part. When it adopts constant-voltage control, the converter is employed to keep the DC link voltage at the reference value by the current control loop which is the same as the inverter's control strategy used in the MPPT control (shown in the Figure 7). When it works in droop control mode, the droop characteristic is similar to the characteristic introduced in the Section 3.3.1. The control loops are illustrated in the Figure 7. The droop control also realizes voltage command tracking by the current loop which is used in MPPT control. The difference is that the reference value of the DC voltage is calculated based on the droop equations.

3.5.2 Active power filter

As nonlinear loads in the prosumer will deteriorate the power quality, the APF is used to eliminate the current harmonics and improve the power quality. The control diagram is shown in the Figure 8. The current of the nonlinear loads is used for the fundamental component calculation based on the orthogonal characteristic of trigonometric function. Then the harmonic component is obtained by subtraction of fundamental component from original current signal. This component will be the reference output current of the inverter. The current

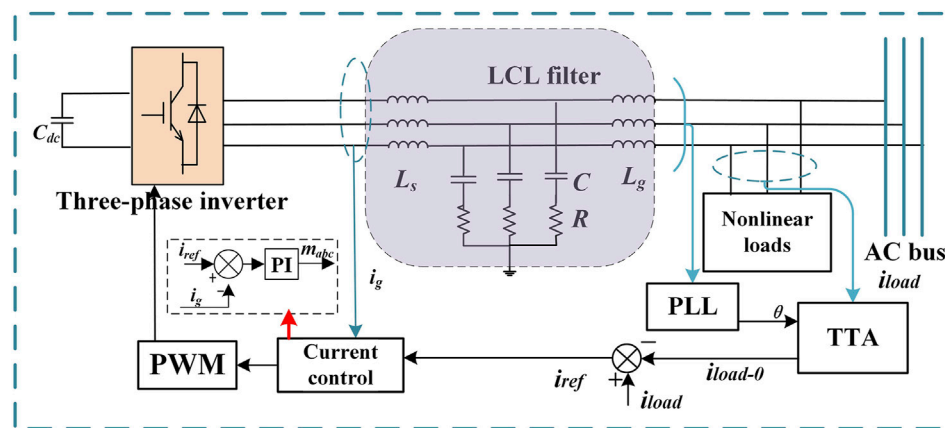


FIGURE 8
The control diagram of APF.

control is realized by the single current control loop. Therefore, the APF will output the harmonic current to eliminate the influence of the nonlinear loads.

3.6 Multi-type loads

There are multi-type loads in the prosumer. In the DC part, the constant power loads are connected to the dc-bus with the buck converters to keep the power constant. The output voltage of the buck converter is maintained at a constant value to keep the power constant. In the AC part, the loads include linear load, nonlinear load and electrical machine. The linear load is composed of linear elements including resistance, inductance and capacitance and in nonlinear load the linear elements are connected to the ac-bus by the three-phase non-controlled rectifier, which will generate odd harmonics. The electrical machine in the prosumer is the permanent magnet synchronous motor.

the power grid, the voltage in the ac-bus will be decided by the grid voltage in the bus. The prosumer can exchange power with the grid. When the slight oscillation is occurred in the grid, a part of the DGs in prosumer can provide voltage and frequency support for the grid. In this mode, the primary control objective is to ensure the stable connection of the DGs and guarantee reasonable profit. In the meantime, the enough reserve capacity of the prosumer is also necessary. When the grid voltage fluctuates in a wide range with the significant change of the power distribution, the prosumer should switch from normal grid-connected mode to grid-fluctuation mode. Compared to normal grid-connected mode, more DGs will participate in the voltage regulation. The number of the facilities that provides auxiliary service for the grid will be increased. The prosumer in this control mode will effectively contribute to the fluctuation reduction of the voltage and frequency in the bus.

4.2 Control of multi-type generations in different modes

With the change of the prosumer's operation objective, the control modes of the DGs will be changed (listed in Table 1). Both in the two kinds of operation modes, multiple equivalent controlled voltage-sourced generators are paralleled in the AC bus of prosumer. The integrated renewables and battery-storage inverter is worked in v-VSG control mode and the output voltage is equal to the grid voltage in PCC. Under normal conditions, the voltage in PCC will be equal to the rated value. Therefore, the inverter will supply rated power to the system. The micro-generator will supply constant power and its output voltage will be unchanged. The PV inverters and battery-storage inverter adopt current-controlled control method. PV2 adopts MPPT control, while PV3 and ES2 both work in CPQT control

4 Prosumer mode switch control

The prosumer can operate in different modes, including normal grid-connected mode and grid-fluctuation mode. The control strategy of the DGs in prosumer will change according to the system demand. In this chapter, the operation modes of the prosumer will be introduced.

4.1 Mode classification

As introduced before, two kinds of main operation modes are considered in the prosumer. When the prosumer is connected to

TABLE 1 Control strategies of the DGs in different modes.

Control mode	Generations							
	AC part					Interlinking converter	DC part	
	Integrated PV and ES inverter	PV2	PV3	ES2	Micro-turbine		PV4	ES3
Grid-connected mode	v-VSG control	MPPT control	CPQT control	CPQT control	CPVC control	Droop control	MPPT control	Constant-voltage control
Grid-fluctuation mode	v-VSG control	NVD-APC control	i-VSG control	Droop control	CPVC control	Constant-voltage control	MPPT control	Droop control

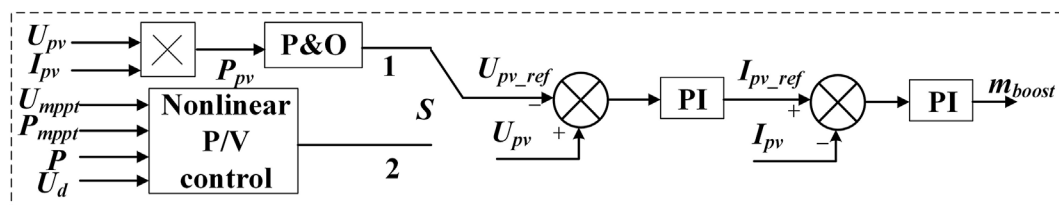


FIGURE 9

The control diagram of the mode switch of PV2.

mode. In DC part, the PV generator works at the maximum power point and the battery will operate in constant-voltage control mode. In this mode, the interlinking converter adopts droop control to reduce the DC voltage fluctuation.

In the grid-fluctuation mode, more generators will provide voltage and frequency support. The PV2 will adopt NVD-APC control to support the grid voltage in PCC. The i-VSG control and droop control strategy are employed in PV3 and ES3, respectively. Both inverters will take part in the frequency modulation and peak regulation. What's more, the integrated PV and ES inverter, and PV3 that adopts VSG control will contribute to the improvement of the frequency dynamics. At the same time, the interlinking converter adopts constant-voltage control to reduce the impact on the PCC voltage. The battery-storage in the DC part will take the voltage-regulation by adopting droop control.

4.3 Mode switch control strategy

As introduced before, when the prosumer switches from normal grid-connected mode to grid-fluctuation mode, the control strategy of several converters should be changed. The mode-switching diagram is shown in the Figures 2,3,5–7. The central controller will receive the fluctuation signal detected in

PCC. If the fluctuation is out of a limit for some time, the prosumer will start mode-switching process and the switch signal will be transferred to the converters that includes the PV inverters, the ES inverter, the interlinking converter and the ES generator in DC part. In grid-fluctuation mode, PV2 switches from MPPT control mode to NVD-APC control mode. The control loops of the two strategies are the same, while the power control is realized by the boost converter and the inverter is used to stabilize the DC voltage in both modes. Therefore, when the converters receive the mode-switching signal, the boost converter only needs to change the reference-calculation algorithm from P&O algorithm to NVD-APC algorithm. The control diagram is shown in the Figure 9. The switch S will be thrown from point1 to point2. Similarly, the mode-switching process of PV3, interlinking converter and ES3 is realized by changing the reference-calculation step through the switches. For PV3, the central controller introduces the SG characteristics emulation part to calculate the reference power as shown in the Figure 3. In the meantime, the constant reference value of the active power and reactive power of ES2 will be replaced by the calculation results based on the Eq. 11. The reference DC voltage of the interlinking converter will be replaced by the constant value, while the droop characteristic will be introduced in the battery-storage converter reference calculation (shown in the Figures 6,7).

TABLE 2 Simulation parameters.

Electrical equipment	Parameters	Value
Power grid	rated grid voltage $U_{g,n}/V$	311
	rated grid frequency $f_{g,n}/Hz$	50
	line resistance R_g/Ω	0.02
	line inductance L_g/mH	0.08
Integrated PV and ES inverter	rated frequency f_{n1}/Hz	50
	rated voltage U_{n1}/V	311
	rated active power P_{n1}/kW	30
	rated reactive power $Q_{n1}/kVar$	8
	DC-link reference voltage U_{dc_ref1}/V	750
	active power droop coefficient D_{p1}	6,000
	reactive power droop coefficient D_{q1}	500
	reactive power integral coefficient k_{q1}	15
	virtual inertia J_1	2
PV2	rated active power P_{n2}/kW	8
	DC-link reference voltage U_{dc_ref2}/V	750
	P/V droop coefficient k_{p1}	200
	P/V droop coefficient k_{p2}	400
PV3	rated frequency f_{n3}/Hz	50
	rated voltage U_{n3}/V	311
	rated active power P_{n3}/kW	15
	rated reactive power $Q_{n3}/kVar$	8
	DC-link reference voltage U_{dc_ref3}/V	750
	active power droop coefficient D_{p2}	3,000
	reactive power droop coefficient D_{q2}	500
	reactive power integral coefficient k_{q2}	15
	virtual inertia J_2	1
	rated frequency f_{n4}/Hz	50
	rated voltage U_{n4}/V	311
	rated active power P_{n4}/kW	15
ES3	rated reactive power $Q_{n4}/kVar$	4
	DC-link reference voltage U_{dc_ref4}/V	750
	active power droop coefficient D_{p3}	3,000
	reactive power droop coefficient D_{q3}	250
micro-turbine	rated frequency f_{n5}/Hz	50
	rated voltage U_{n5}/V	311
	rated active power P_{n5}/kW	40
Interlinking converter	droop coefficient k_1	0.1
	DC-link reference voltage V_{dc_ref2}/V	750
ES4	droop coefficient k_2	0.1
	DC-link reference voltage V_{dc_ref1}/V	750

(Continued on following page)

TABLE 2 (Continued) Simulation parameters.

Electrical equipment	Parameters	Value
	maximum charging current I_{cha_max2}/A	50
	maximum discharging current I_{dis_max2}/A	100
DC part	rated dc-bus voltage V_{dc_n}/V	750
Central controller	maximum voltage variation	$\pm 3\%$
	maximum frequency variation	$\pm 0.5\%$

5 Network simulation of prosumer with multi-type generations

In this section, the simulation based on Matlab/Simulink is used to verify the effectiveness of the proposed coordinated operation strategy in the prosumer with multi-type generations. The prosumer can stably operate in different modes and the seamless mode switch is also realized. The structure of the prosumer is shown in the Figure 1 and the control modes of the multiple generations are introduced in the Table 1 in detail. The simulation parameters are listed in the Table 2.

5.1 Normal grid-connected mode

The control modes of the prosumer's generations in normal grid-connected mode have been introduced in the last section and are listed in Table 1. In this mode, the output voltage and current of the integrated PV and ES inverter will keep stable and their output voltage will be decided by the grid voltage.

The waveform of the voltage and current in PCC is shown in the Figure 10A. At 2s, the light intensity of PV1 is decreased and the maximum power is changed as shown in the Figure 10B. The power fluctuation of PV1 is eliminated by ES1 and the DC link voltage keeps stable, where the output power of PV1 is represented by P_{PV1} and the DC link voltage is represented by U_{dc1} . When $t = 3.5s$, the linear load in the prosumer increases and the light intensity of PV1 and PV2 is reduced, which will lead to the voltage reduction in the ac-bus. As introduced in Section 3.2, the integrated renewables and battery-storage inverter increases its output reactive power to support the voltage at 3.5s. The simulation result is shown in the Figure 10C, where the output active power and reactive power of the integrated PV and ES inverter are represented by P_l and Q_l respectively. The maximum power of PV1 and PV2 is changed as shown in the Figure 10D, where P_{PV2} represents the output power of the PV2 and the output voltage and current of the PV2 inverter are represented by U_{m2} and I_{m2} separately.

At the same time, the output power of the generations in CPQT control mode will keep unchanged and the results are shown in the Figures 10E,F, where the output power of PV3 and ES2 are represented by P_{PV3} Q_{PV3} and P_{ES2} Q_{ES2} respectively. The output voltage and current of PV3 inverter are represented by U_{m3} and I_{m3} and the output voltage and current of ES2 inverter are represented by U_{m4} and I_{m4} . In the DC part, the battery-storage converter works in constant-voltage control mode and its output voltage V_{dc1} keeps at the rated value. The PV4 adopting MPPT control keeps working at the maximum power point. In grid-connected mode, the interlinking converter adopts droop control and operates as the rectifier. What's more, at 2s, the local load in the DC part is increased and the reference DC voltage of the interlinking converter is increased to reduce the voltage variation according to the droop characteristic shown in the Figure 7. The simulation result is shown in the Figure 10G, where the voltage in dc-bus is represented by V_{dc} and the DC link voltage of the interlinking converter is represented by V_{dc2} . In addition, the effectiveness of the proposed APF is verified in the Figure 10H. When $t = 2s$, the APF is added to the prosumer and the harmonics of the voltage and current in PCC of the prosumer is effectively eliminated at 2s.

As shown in the simulation results, the prosumer with multi-type generations can operate in normal grid-connected mode stably under the proposed coordinated control strategy. Moreover, when there is fluctuation in the prosumer caused by load variation and illumination change, the integrated renewables and battery-storage inverter can regulate its output power to provide frequency and voltage support.

5.2 Grid-fluctuation mode

In grid-fluctuation mode, more generations will provide auxiliary service for the system and the control modes of the generations are introduced in Table 1. The waveform of the voltage U_{PCC} in PCC is shown in the Figures 11A,B, where U_{d_g} is the voltage amplitude of U_{PCC} . At 3s, there's deviation between the grid voltage in PCC and the rated value, while the voltage is

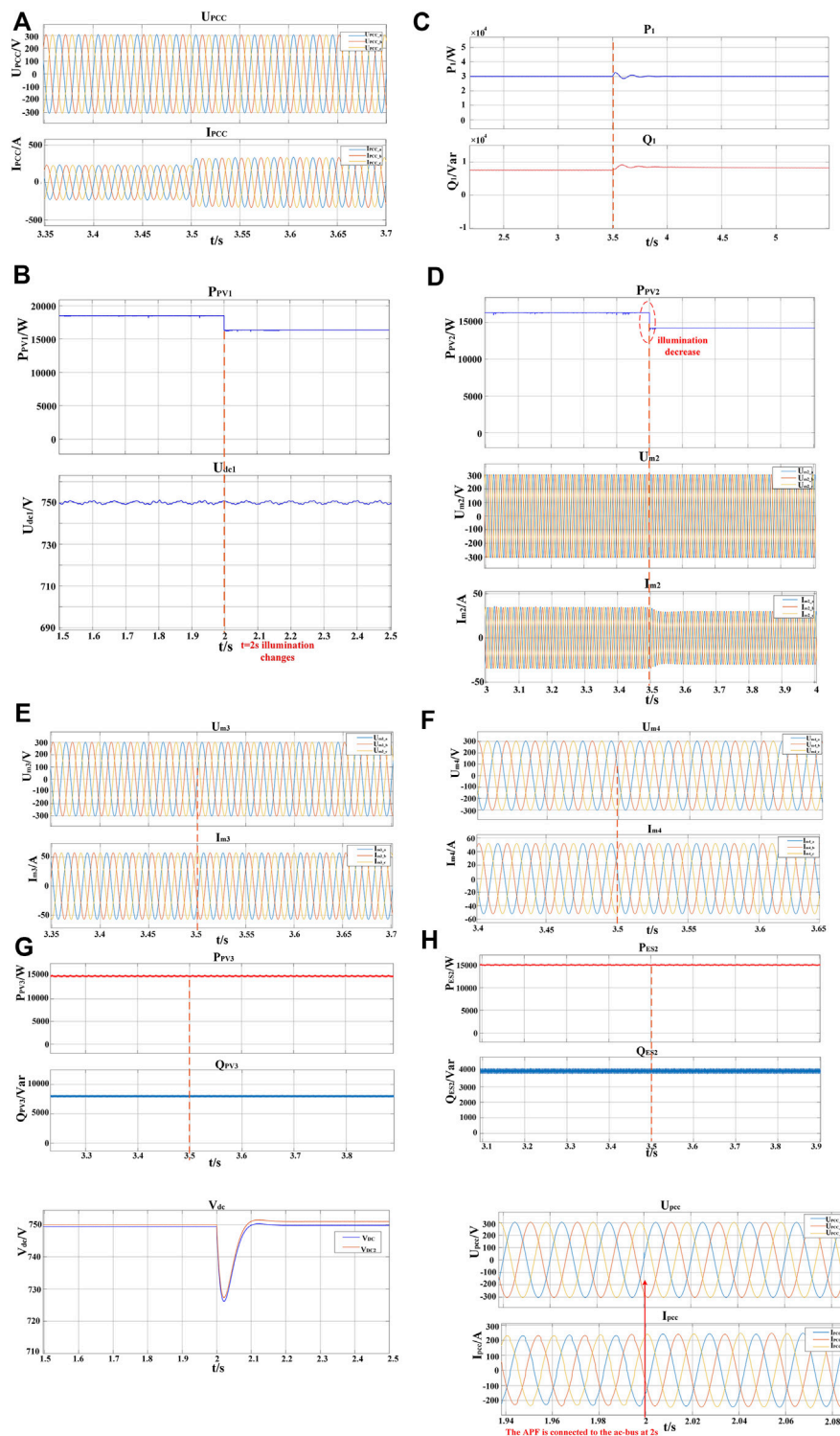


FIGURE 10

The output of the converters in the prosumer in normal grid-connected mode: (A) Voltage and current in PCC; (B) PV1's output power and the DC link voltage; (C) Output power of the integrated inverter; (D) Output of PV2; (E) Output of PV3; (F) Output of ES2; (G) The comparison between the DC link voltage of the interlinking converter and the voltage in dc-bus; (H) The voltage and current in PCC.

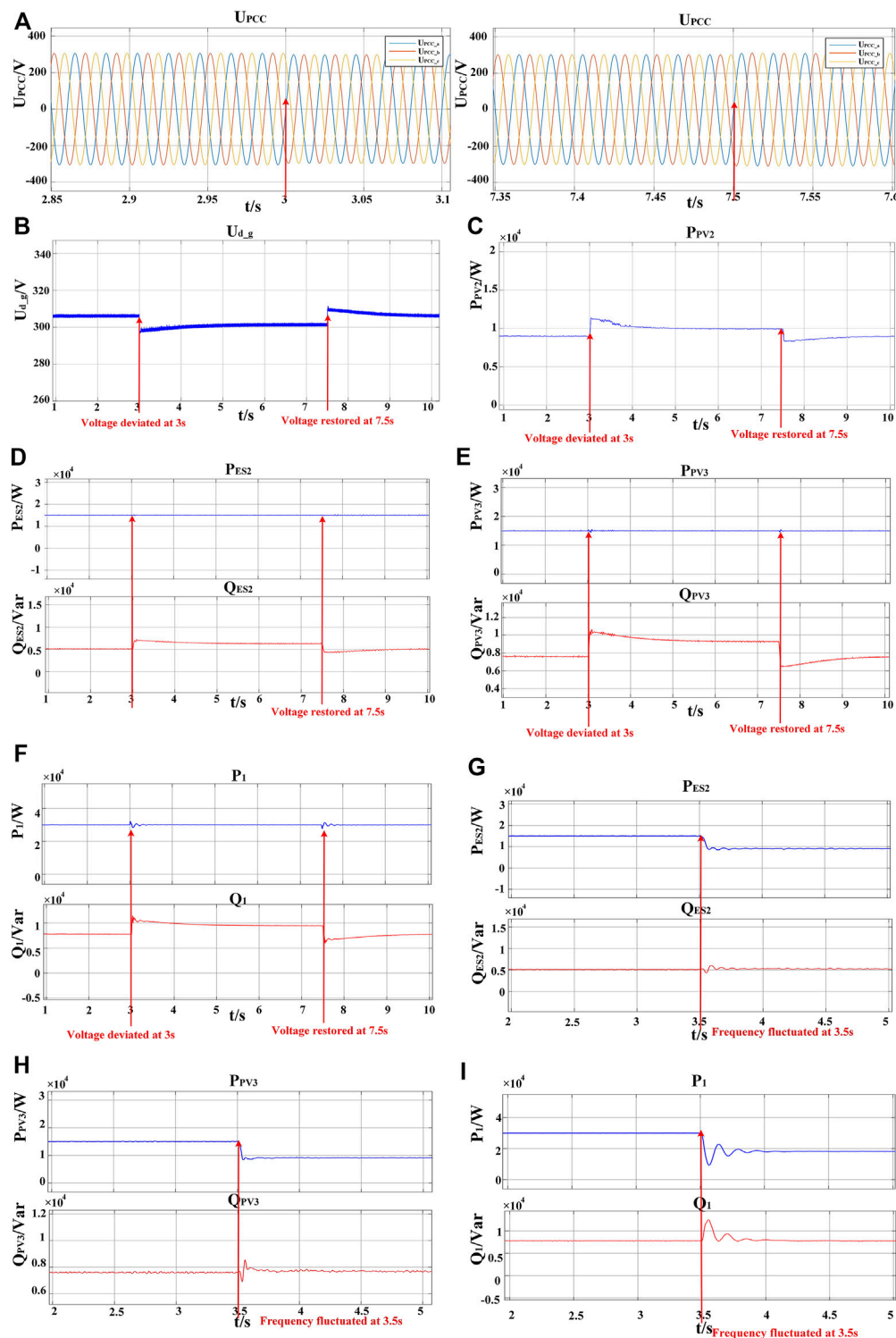


FIGURE 11

The output of the DGs in the prosumer in grid-fluctuation mode: (A) The voltage in PCC; (B) The amplitude of the voltage in PCC; (C) The output active power of PV2; (D) The output active power and reactive power of ES2; (E) The output active power and reactive power of PV3; (F) The output active power and reactive power of the integrated inverter; (G) The output active power and reactive power of ES2; (H) The output active power and reactive power of PV3; (I) The output active power and reactive power of the integrated inverter.

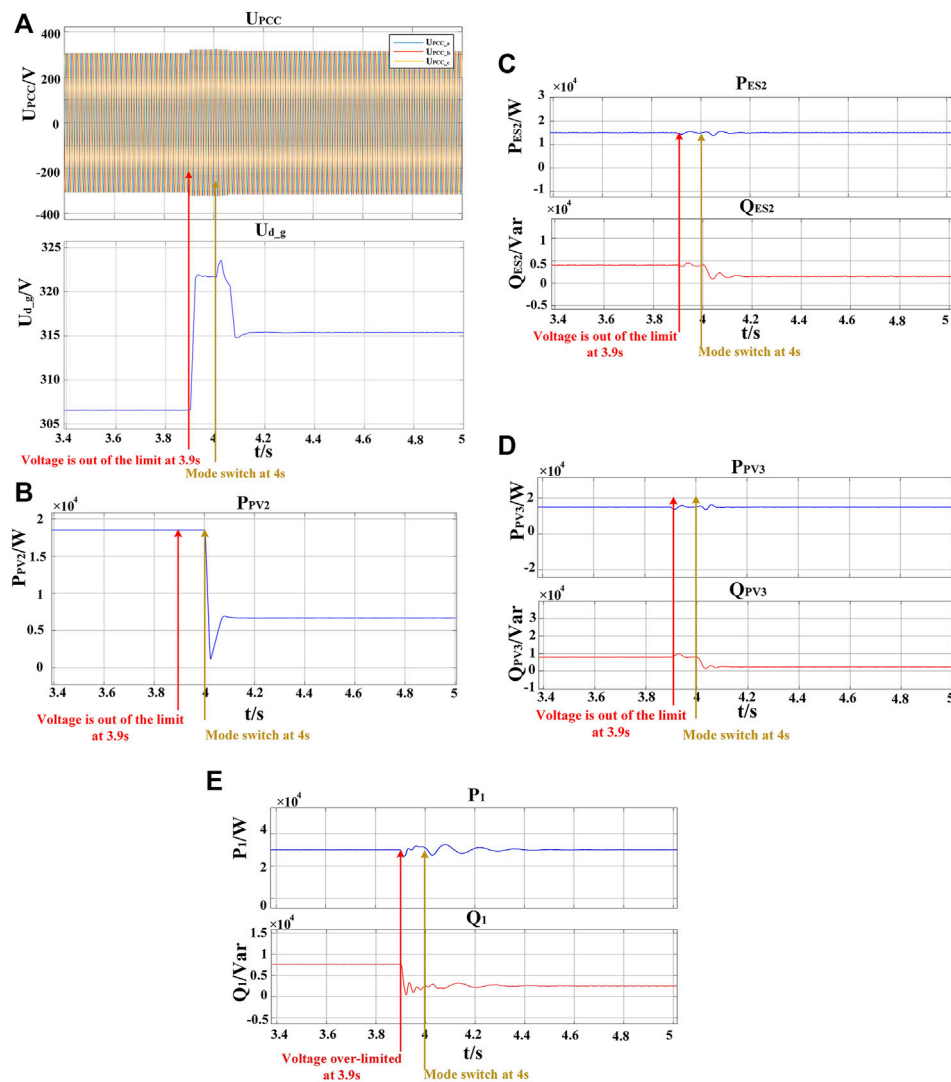


FIGURE 12

The output of the DGs in the prosumer during mode switch: (A) The voltage in PCC during mode switch; (B) The output active power of PV2 during mode switch; (C) The output active power and reactive power of ES2 during mode switch; (D) The output active power and reactive power of PV3 during mode switch; (E) The output active power and reactive power of the integrated inverter during mode switch.

restored to the rated value at 7.5s. As introduced in the Section 4.2, there are four generations in the AC part participate in the frequency modulation and peak regulation. When $t = 3$ s, the output active power of PV2 is increased as shown in the Figure 11C, where P_{PV2} represent its output active power. The integrated inverter, PV3 and ES3 all improve their output reactive power to support the voltage and the simulation results are shown in the Figures 11D–F. In addition, the droop coefficients of the three generations are proportional to their capacities to ensure the proportional variations of their output power. At 7.5s, the fault is cleared, and the output power of the

above generations returns to rated value. Furthermore, to verify the frequency-supporting function of the inverters, in the Figures 11G–I the frequency is increased to 50.3 Hz at 3s. The integrated inverter, PV3 and ES2 reduce their output active power to provide frequency support for the grid.

Hence, the effectiveness of the prosumer's grid-supporting function is verified by the simulation results. Compared to normal grid-connected mode, more generations adopt grid-supporting control strategy, and the power quality can be effectively improved in grid-fluctuation mode.

5.3 Simulation validation of mode-switching control strategy

The mode-switching control strategy proposed in the Section 4.3 is verified by simulation results in this section. The waveform of the grid voltage in PCC is shown in the Figure 12A, where U_{PCC} represents the three-phase voltage in PCC and U_{d-g} represents the voltage amplitude of U_{PCC} . At first, the prosumer operates in normal grid-connected mode. When $t = 3.9s$, the grid voltage is increased to 322.5 V and the voltage deviation is more than the limit listed in the Table 2. The prosumer starts mode-switching process at 4s. The simulation results are shown in the Figure 12. The output power of the generations is changed to support the voltage. Meanwhile, the output voltage of the battery converter ES3 in the DC part is changed and the output DC voltage of the interlinking converter is kept at the rated value. When $t = 4.2s$, the prosumer operates in grid-fluctuation mode stably and the grid voltage in PCC is decreased to 315.5 V. Therefore, the correctness of the proposed mode-switching control strategy is validated by simulation. When there's over-limited voltage fluctuation in PCC, the prosumer will start mode-switching process and switch from normal grid-connected mode to grid-fluctuation mode to provide grid-supporting service.

6 Conclusion

This paper establishes an AC/DC hybrid prosumer with multi-type facilities and proposes the coordinated operation control strategies in different modes. The prosumer can operate in both the normal grid-connected mode and grid-fluctuation mode and the operation modes of the distributed generations will be changed accordingly. In the normal grid-connected mode, the prosumer stably connects to the power grid and provides active support. In the grid-fluctuation mode, most generations in the prosumer can participate in the frequency modulation and peak regulation with respective control strategies. Moreover, the mode-switching control strategy is proposed to make the prosumer switch from normal grid-connected mode to grid-fluctuation mode without undesired disturbance after undesired excessive grid fluctuation. With the proposed method, the prosumer can operate in different situations to support the integration of high-penetration renewables. The correctness of the proposed coordinated

operation strategies is verified by the simulation results. The coordinated operation control strategies in different modes in this paper is proposed to provide suggestions for the grid connection of the prosumer with high renewables and multi-type energy sources. Under the proposed control strategies, the prosumer can provide active support for the power grid and the renewable energy utilization can be effectively improved (Wang et al., 2021).

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

XH contributed to the conception of the study and performed the data analyses and wrote the manuscript. LM performed the simulation validation. CS contributed significantly to analysis and manuscript preparation.

Funding

This paper is supported by State Grid Hebei Electric Power Cooperation (under Grant: kj 2021-004).

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OPEN ACCESS

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SPECIALTY SECTION
This article was submitted to Process and
Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 27 December 2022
ACCEPTED 20 January 2023
PUBLISHED 01 February 2023

CITATION
Yang K, Guo Y and Fu X (2023), Opinion on
intra-provincial medium and long-term
electricity market considering available
transmission capacity.
Front. Energy Res. 11:1132224.
doi: 10.3389/fenrg.2023.1132224

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Opinion on intra-provincial medium and long-term electricity market considering available transmission capacity

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KEYWORDS

medium and long-term electricity market, available transfer capability, centralized auction transaction, matchmaking transaction, listing transaction, negotiated transaction

1 Introduction

In 2021, China proposed to promote the construction of the medium and long-term (M-L) electricity market and accelerate the construction of the national unified electricity market (Huang and Li, 2022). Each province had also issued M-L electricity market trading rules. M-L electricity market refers to the multi-year, annual, quarterly, monthly, weekly and multi-day electricity wholesale transactions carried out by power generation companies, power consumers, electric power companies, and other market entities through the negotiated transaction, centralized auction transactions, and other market-oriented methods. At present, the M-L electricity market in various provinces in China mainly carries out electrical energy transactions. The organization forms of the transaction include auction transactions and negotiated transactions. However, various organization forms are generally not considering network constraints during market clearing (Guo et al., 2020). This can lead to a series of problems, such as the power dispatching institution having to take a long time to do the security assessment, and the time of transaction organizations being longer. Moreover, the adjustment rate of the first market clearing result is relatively high because network constraints are not considered and the security assessment time is long (Xia et al., 2020). Due to the uncertainty of new energy, the market needs to provide sufficient adjustment opportunities, so the M-L market must have the ability to start the market periodically. But a high adjustment can make it difficult for the M-L market to carry out full-cycle and high-frequency transactions. The demand for normalized transactions in the M-L market cannot be met. Therefore, to take high-frequency transactions and security assessment into account in the market, it is necessary to consider the network's available transfer capability (ATC) constraints in M-L electricity transactions.

The total transfer capability subtracts the transmission reliability margin and capacity benefit margin, and the remaining part is the available transmission capacity. It represents the amount of transmission capacity left in the network that could be used commercially. Domestic and foreign scholars have already conducted a wide range of studies on the M-L electricity market and ATC methods. The calculation methods of ATC include the method based on power flow and intelligent algorithms. Mohamed et al. provided a comprehensive review of the calculation methods of available transmission capacity (Mohammed et al., 2019). In the inter-provincial M-L electricity market research, Zeng et al. simplified the AC/DC hybrid network by using the sensitivity analysis method. Then, they considered the ATC constraints of the equivalent network and established a market optimization clearing model of centralized auction transactions (Zeng et al., 2020a). In addition, Zeng et al. aimed at the problem of market coupling in the national unified electricity market. They proposed three bi-level clearing models

which were suitable for different market stages. They considered the ATC constraints of AC/DC networks and established the market clearing model for the inter-provincial market (Zeng et al., 2020b). Fu et al. also took into account the security constraints of the network in the M-L electricity market. On the strength of power transfer distribution factors, they calculated the available transfer capability of the grid through the DC power flow calculation method. Then they established the M-L electricity market transaction clearing model, which could ensure the transactions pass the security assessment (Fu et al., 2022). Europe is the forerunner in electricity market reform. In the process of coupling various European regions, European Union developed a Pan-European Hybrid Electricity Market Integration Algorithm (EUPHEMIA) (Lam et al., 2018). At the initial stage, EUPHEMIA adopted the ATC method to calculate the allocation of cross-regional capacity. This method is still used in most market areas today (The European Network of Transmission System Operators for Electricity, 2021). Chatzigiannis et al. established an elaborate model. The model considered a large number of network constraints and market constraints in European Power Exchanges (PXs). These constraints included ATC and flow-based (FB) network constraints (Chatzigiannis et al., 2016). Le et al. pointed out that Europe had completed day-ahead market coupling, and the next task was establishing continuous trading in the intraday market. They proposed an advanced algorithm that could coordinate continuous trading and discrete auction. The algorithm could realize the market clearing at any level of coordination between the two trading mechanisms (Le et al., 2019). Gunkel et al. made a comparative analysis of various models of the power transmission system. They argued that the net transmission capacity (NTC) method was conservative in calculating line capacity (Gunkel et al., 2020). Makrygiorgou et al. pointed out that the ATC method still occupied a dominant role in European cross-border transactions. Their study compared these two methods. They argued that the two methods had the same objective function in the problem of European market coupling and blocking management, and the main difference was the constraint conditions (Makrygiorgou et al., 2020). The ATC method could provide an easier way for transactions, but the utilization rate of power transmission capacity was not as good as the FB method.

In summary, the current research on the ATC method has been relatively mature. Many studies have analyzed the application of the ATC method in China's inter-provincial M-L electricity market. However, as for the intra-provincial M-L electricity market, there is still a lack of relevant research. The existing research has provided a sufficient experience for the research of the intra-provincial electricity market. Therefore, China must research intra-provincial M-L electricity market clearing models considering ATC constraints. This can lay the foundation for realizing the connection of electricity markets between different regions and building a unified national electricity market.

2 Intra-provincial M-L transaction mechanism considering ATC

Available transmission capacity represents the amount of transmission capacity left in the network that could be used commercially. On the one hand, power grid operation is complicated and uncertain due to various factors. On the other

hand, the proportion of new energy with intermittent, random, and volatile characteristics in the power grid will gradually increase, and will gradually enter the power market for trading in the future. The peak load of the power system is often close to the transmission capacity limit of the grid, which will make the situation of the grid more complicated. Therefore, the transmission capacity of the power network must be calculated frequently to ensure the stability of high-frequency power transactions.

At present, the M-L electricity market in various provinces mainly conducts electrical energy transactions. The organization forms of the transaction include auction transactions and negotiated transactions. Auction transactions include centralized auction transactions, matchmaking transactions, and listing transactions. The process organization of various transactions is different. Therefore, to consider the application of ATC in the M-L market, we should analyze the four transaction modes separately. The intra-provincial M-L transaction mechanisms considering ATC constraints established in this paper are shown in Figure 1. The following is an analysis of these four trading methods.

Centralized auction transaction: Centralized auction transaction requires all the market entities to declare the information including the amount of electricity and price in different periods on the power trading platform. Then the power exchange center organizes the uniform clearing. Finally, the transaction results are formed after checking by the power dispatching institution. Generally, market transaction clearing uses the integrated method of two models. One model is security-constrained unit commitment, and the other model is security-constrained economic dispatch. Currently, the M-L centralized auction transaction generally only sets price and electricity constraints. Therefore, under the new transaction mechanism. To form the trading result with the curve at different time segments, the ATC constraints of the network should be taken into account in the market transaction clearing model.

Matchmaking transaction: During the opening period of the matchmaking transaction, each market entity can submit the bidding information at any time, and the power exchange center carries out the rolling matchmaking transaction according to the principle of time first and price first. Unlike the unified clearing of centralized auction transactions, the matchmaking transaction will be cleared all the time. Whenever a piece of bidding information meets the requirements, a deal is struck. Therefore, under the new transaction mechanism, the matchmaking transaction should consider the ATC constraints of the transmission network in each matching clearing. After completing a transaction, the ATC constraints of the transmission network are updated on a rolling basis to provide constraints for the next transaction.

Listing transaction: In the listing transaction, a market entity (power buyer or the power seller) puts forward the bidding information, including power purchase information, power sale information, or the power energy and price at different periods of the contract. After the power exchange center conducts the market clearing of the application information, the listing transaction result will be formed. During the listing transaction period, after the listing entity completes the listing operation, the delisting entity shall proceed to delist operation. Therefore, under the new transaction mechanism, there are two aspects needed to think about the ATC constraints of the transmission network in the listing transaction. On the one hand, the generating capacity of the unit and load demand level need to be considered when the power exchange center is clearing to form the

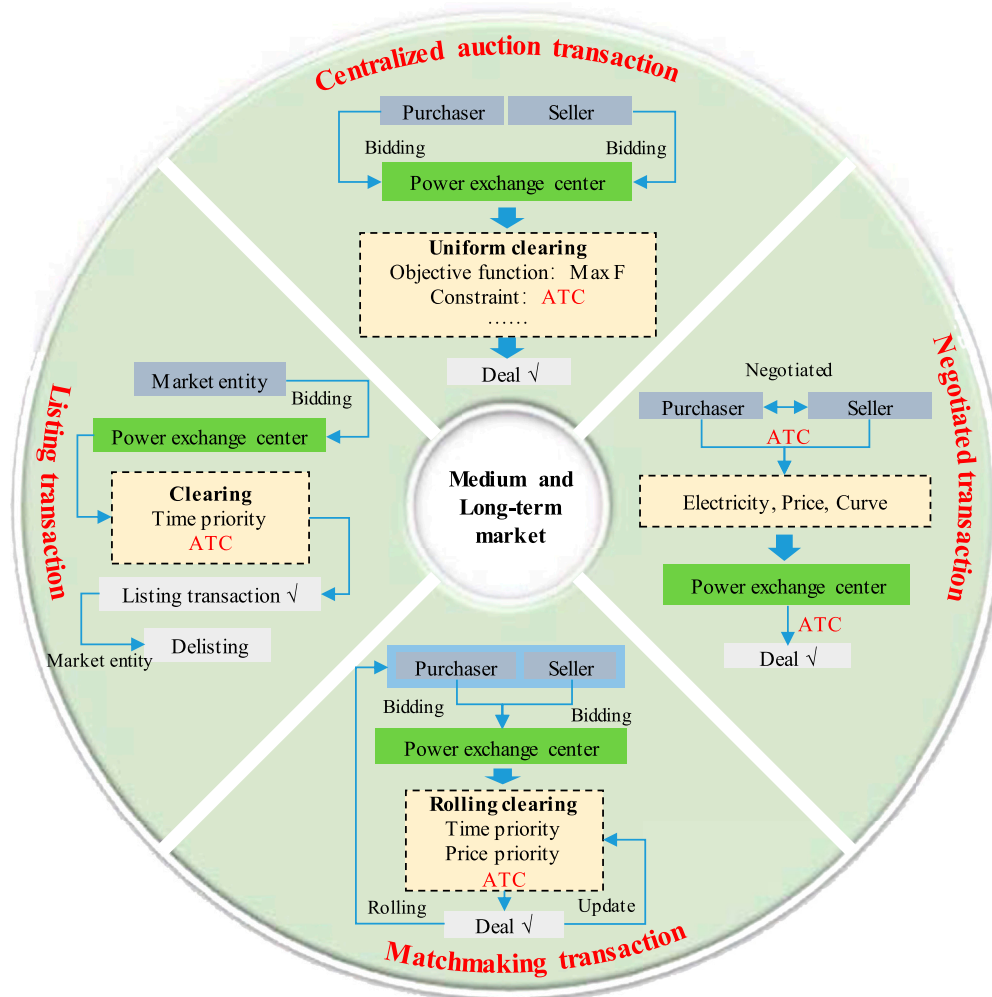


FIGURE 1
Intra-provincial M-L transaction mechanisms considering ATC.

listing transaction results. On the other hand, when the delisting entity proceeds with the delisting operation, it should not only ensure that the delisting power or the maximum power shall not exceed the upper limit of the listing transaction but also ensure that the trading results after delisting shall not exceed the transmission capacity limit of the power grid. Therefore, the ATC constraints of the network should be considered before and after the listing transaction.

Negotiated transaction: In the negotiation transaction, market entities independently negotiate the electricity and price of the transaction. The negotiated transaction shall be declared and confirmed by one party in the power exchange center. After that, the power trading center clears the negotiation result and submits it to the power dispatching institution for security assessment, thereby forming the final trading result. Therefore, under the new transaction mechanism, the power exchange center shall publish the ATC of the transmission network in advance before the opening of the bilateral negotiation transaction, to guide the trading quantity and the method of the curve decomposition of the two parties. When clearing the negotiated electricity, the power exchange center should also consider the ATC constraints, to ensure that the electricity transaction curve reached meets the operation demand of the grid.

3 Discussion

The application of technical methods requires a complete market mechanism to cooperate with each other. At present, the reformation of the electricity market in China is in the initial stage. In order to realize the application of the ATC method in the intra-provincial M-L electricity market. The electricity market mechanism requires to be further refined. In-depth research is still needed on the following aspects. First of all, it is necessary to realize the connection of trading between different regions. This requires close coordination between the power exchange center and the power dispatching institution in various regions. Second, the transaction of the M-L electricity market includes different time-scale, such as annual transactions, quarterly transactions, monthly transactions, and multi-day transactions. Therefore, a full-cycle transaction mechanism of the M-L electricity market needs to be established. Gradually realize the connection between the M-L market with the spot market. Finally, the power exchange center submits the market clearing result to the power dispatching institution. The power dispatching institution returns the data to the power exchange center, such as the available transmission capacity. Through the collaboration between the two,

real-time updates of the grid's available transmission capacity can be realized. The M-L electricity market transactions will have two characters, full-time and high-frequency. Therefore, there are many benefits to considering the available transmission capacity constraints in M-L electricity transactions. On the one hand, it can shorten the overall transaction time and increase the frequency of the transaction. On the other hand, it also can provide crucial technical support for new energy participation in the M-L electricity market.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

Funding

The research is supported by the State Grid Corporation of China: Research on Key Technologies of Intra-provincial Medium and Long

Term Transaction Considering Available Transfer Capacity (No. 5108-202218280A-2-290-XG).

Conflict of interest

YG was employed by China Electric Power Research Institute.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to
Process and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 14 December 2022

ACCEPTED 01 March 2023

PUBLISHED 16 March 2023

CITATION

Chen W, He H, Liu J, Yang J, Zhang K and
Luo D (2023), Photovoltaic power
prediction based on sliced bidirectional
long short term memory and
attention mechanism.
Front. Energy Res. 11:1123558.
doi: 10.3389/fenrg.2023.1123558

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Photovoltaic power prediction based on sliced bidirectional long short term memory and attention mechanism

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Solar photovoltaic power generation has the characteristics of intermittence and randomness, which makes it a challenge to accurately predict solar power generation power, and it is difficult to achieve the desired effect. Therefore, by fully considering the relationship between power generation data and climate factors, a new prediction method is proposed based on sliced bidirectional long short term memory and the attention mechanism. The prediction results show that the presented model has higher accuracy than the common prediction models multi-layer perceptron, convolution neural network, long short term memory and bidirectional long short term memory. The presented sliced bidirectional cyclic network has high prediction accuracy by low root mean square error and mean absolute error of 1.999 and 1.159 respectively. The time cost is only 24.32% of that of long short term memory network and 13.76% of that of bidirectional long short term memory network.

KEYWORDS

photovoltaic power generation system, power prediction, sliced recurrent network, bidirectional long short term memory, attention mechanism

1 Introduction

With the progress of the society and the development of the times, human beings rely heavily on new renewable energy. In the 21st century, photovoltaic power generation technology has become the fastest developing new energy technology (Bhang et al., 2019). Therefore, solar energy plays an important role in the development of new energy (Manokar et al., 2018). As a new renewable energy power generation method, solar photovoltaic power generation has the advantages of safety, risk-free, environmental protection and no pollution (Sadamoto et al., 2015). However, photovoltaic power generation is susceptible to the spatio-temporal factors such as weather, season and climate (Hu et al., 2021) (Cao et al., 2022), which makes the power generation of photovoltaic power stations unstable. When the grid is connected, its volatility may cause periodic impact on the power grid and lead to the instability of the power grid. Therefore, it is necessary to formulate adjustment and dispatching plan in advance, coordinate multi-energy sources (Zhang et al., 2022) (Sanjari et al., 2020) and reduce equipment standby before the prediction of the generation power, so as to enhance the security and stability of power grid (Han et al., 2022). In order to make full use of solar energy and reduce the impact of photovoltaic power

stations when the grid is connected, it is necessary to accurately predict the photovoltaic power generation (Si et al., 2020; Jia et al., 2021).

In recent years, people have put forward many methods for photovoltaic power generation prediction. There are common prediction methods based on mathematical methods such as grey theory, time series analysis (Yan et al., 2021), machine learning methods such as support vector regression and BP neural network (Feng et al., 2015). In addition, environmental information like the weather forecast, the satellite image (Wang et al., 2020) and cloud distribution (Fu et al., 2021) are used to support photovoltaic output prediction. The prediction method based on environmental information can achieve high prediction accuracy (Manokar, 2020; Sasikumar and calorimetry, 2020), but these methods need the use of satellite cloud map and large climate database which will increase the cost of the prediction (Chai et al., 2019), multi-layer perceptron (MLP) (Zhang, 2020), convolution neural network (CNN) and long short term memory (LSTM) belongs to the deep learning networks. The CNN network mentioned in document (Kim et al., 2019) needs various auxiliary processing for the photovoltaic prediction, and the prediction effect is not very good. Recurrent neural network (RNN) is suitable for dealing with time series sensitive problems (Lecun et al., 1995). Empirical mode decomposition method in literature (Geddes et al., 2020) and wavelet analysis algorithm mentioned in literature (Lee et al., 2005) decompose the original data into sub data to achieve the prediction. But these methods are relatively complex, which may cause feature loss or reconstruction difficulties in the process of data reorganization. The LSTM network proposed in literature (Xin, 2020) is a typical deep learning model. The prediction accuracy of LSTM model in literature (Huang et al., 2020) is relatively good, these methods can meet the requirements of photovoltaic power generation prediction to a certain extent, but the prediction accuracy still needs to improve. Therefore, based on LSTM network, a prediction method combined sliced bidirectional LSTM with the attention mechanism (SBiLSTM + Attention) is proposed. Testing results indicate the presented Sliced BiLSTM greatly improves the training speed, and the application of the attention mechanism effectively improves the prediction accuracy.

2 Photovoltaic power prediction based on BiLSTM-Attention method

2.1 Influence factors of photovoltaic power generation

Photovoltaic power generation is easily affected by many factors, these factors also affect each other. The most factors like light intensity, ambient temperature, season and wind speed are the most important factors that affect the prediction. The generation power of photovoltaic silicon plate per unit area is determined by Formula 1.

$$P_s = \eta SI (1 - 0.005(t_0 + 25)) \quad (1)$$

In Formula 1, η is the conversion efficiency; $S(m^2)$ is the array area; $I(A)$ is the solar irradiation intensity; $t_0(^{\circ}C)$ is the ambient temperature. For the same group of units, the historical data reflect the impact factors such as converter conversion efficiency and the tilt angle, thus, the problems caused by the time series of the PV

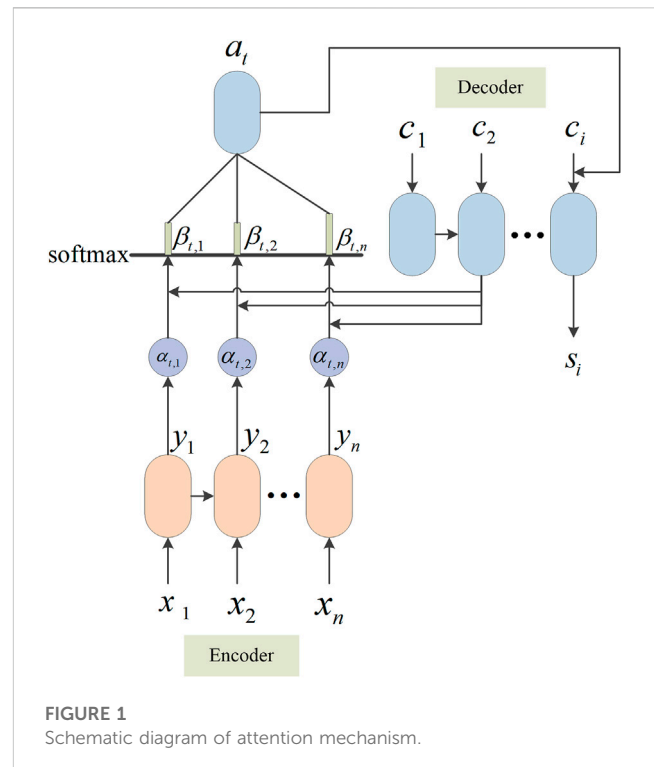


FIGURE 1
Schematic diagram of attention mechanism.

units and the randomness caused by the installation location are solved by using historical data. The method presented in this paper predicts the power generation for moments in the future by using the historical data of generator units and weather factors.

2.2 Attention mechanism

Attention mechanism is a mechanism of distributing weight probability, which can selectively obtain useful information and remove redundant information. The attention mechanism applied in this paper can optimize the model and improve in the training. It effectively solves the problem that the prediction model can not learn a reasonable vector representation due to the too long-time series of the input. The structure of attention mechanism adopted is shown in Figure 1.

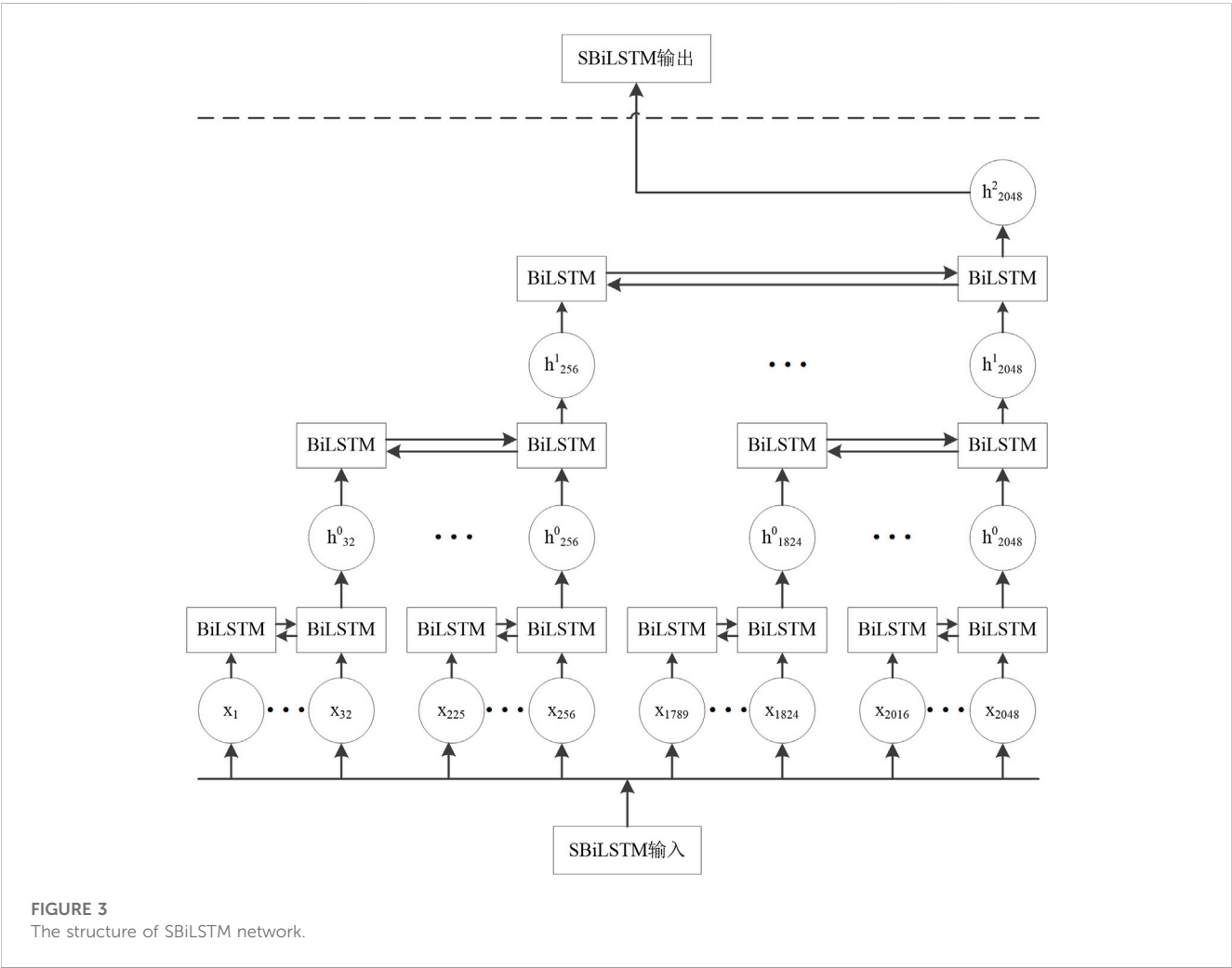
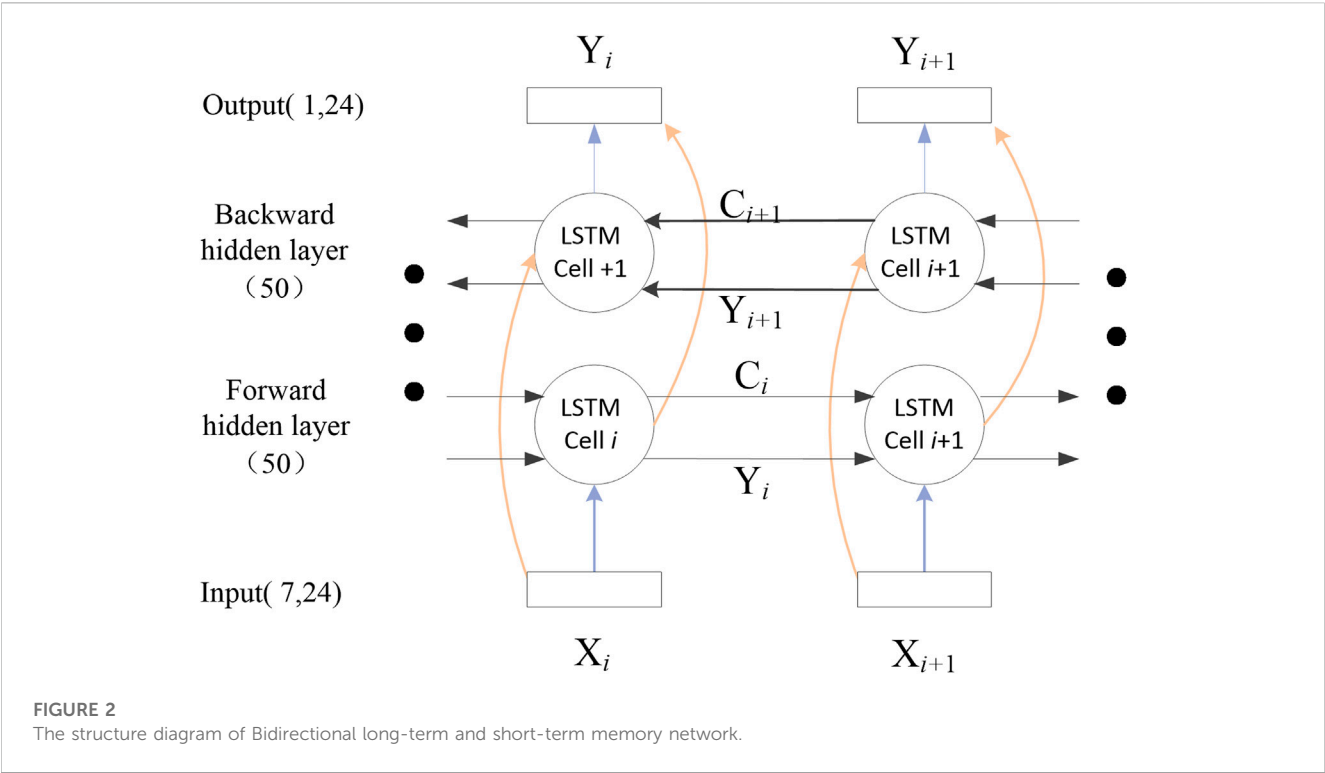
In Figure 1, a_t represents the weight value of the attention mechanism on the output of the hidden layer of the neural network. The calculation formula is shown in Formula 2,

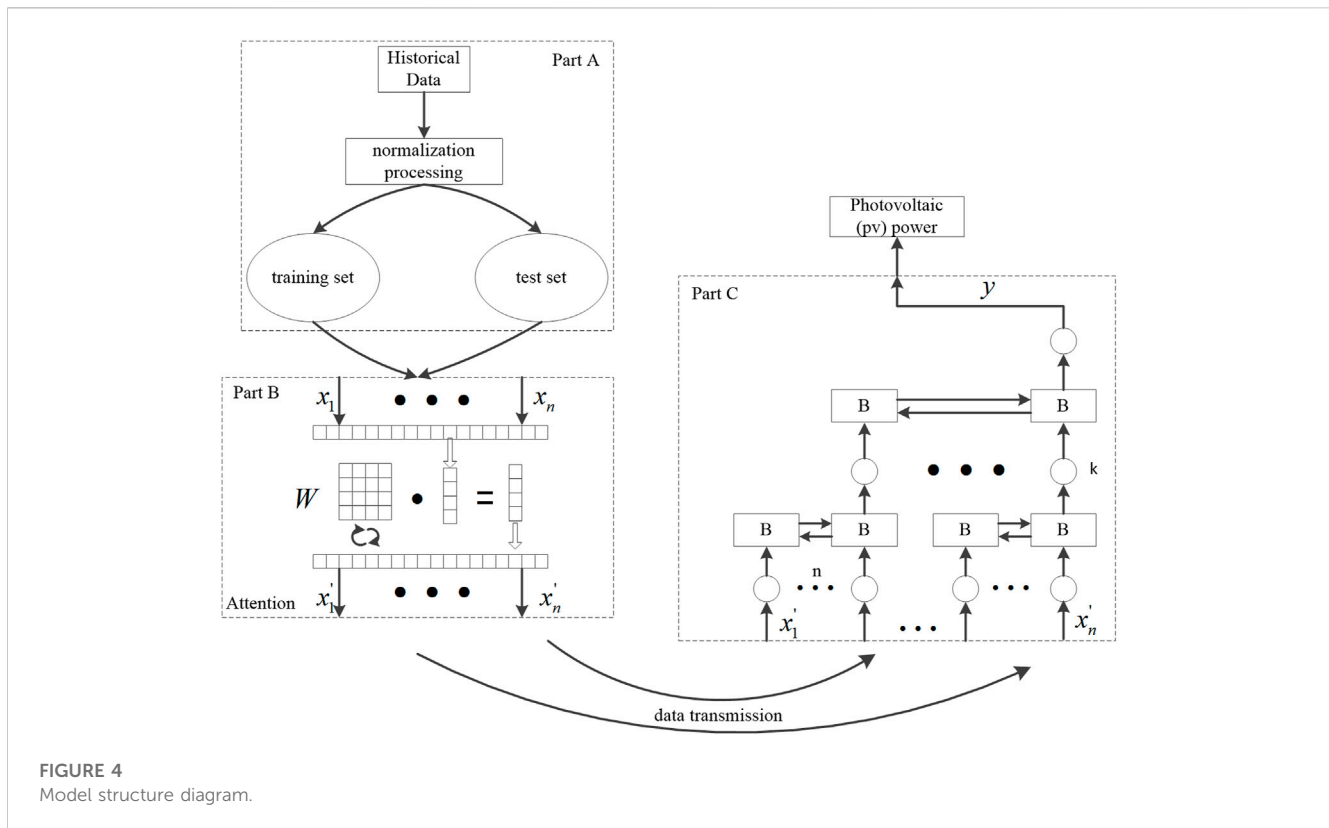
$$a_t = \sum_{i=1}^n \beta_{t,i} \alpha_i \quad (2)$$

The attention score indicates the similarity between the state of the decoder at the previous time and the output of the encoder at present moment. The calculation formula is as follows,

$$\alpha_{t,i} = F(y_i, s_{t-1}) \quad (3)$$

In Formula 3, $\alpha_{t,i}$ indicates the attention score of the decoder at moment t related to the output of the encoder at moment i , y_i represents the output of the encoder at moment i , s_{t-1} represents the





output state of the decoder at moment $t - 1$, and $F(\cdot)$ represents the transformation function.

The probability distribution equation obtained by softmax conversion of attention score is as follows,

$$\beta_t = \text{softmax}(\alpha_t) \quad (4)$$

In [Formula 4](#), α_t represents the attention component of the decoder related to the encoder at time, and β_t is the probability distribution of α_t .

The next step is to combine the input of the decoder at the current time with the attention vector to form a new input for decoding. The calculation formula is as follows,

$$s_t = f([c_t, a_t], s_{t-1}) \quad (5)$$

In [Formula 5](#), c_t represents the input of the decoder at moment t , and $f(\cdot)$ is the transformation function.

The advantage of application of the attention mechanism for the prediction is that the global attention sequence modeling breaks through the limitation of time distance. Therefore, the attention mechanism can be used together with cyclic neural network. First, the attention weight was initialized, historical generating power and total irradiance was set to 30% and 20% respectively, and other influencing factors are set to 10%. Then they will be adaptively adjusted through the training.

2.3 Sliced BiLSTM with attention mechanism

The essence of BiLSTM network is to add a hidden layer on the basis of LSTM network. The structure is shown in [Figure 2](#). There

are two hidden layers, one in the direction from the front to the back and the other is from the back to the front. There is only one output layer. Both hidden layers point to this output layer. Finally, the data of the two hidden layers are integrated. There is no information interaction between the two hidden layers.

In a normal recurrent neural network, each state depends on the input of the previous state, which makes a lot of time costs on training. In order to decrease the time spending, this paper proposes a new sliced recurrent network structure, as shown in [Figure 3](#),

SBiLSTM + Attention network can divide the input sequence into several small sub-sequences by the same length. The cyclic units on each sub-sequence work at the same time. Slicing a long input sequence into small sequences can greatly reduce the training time. Each sub-sequence is divided into N equal length sequences, and then such divisions are operated K times until the minimum sub-sequence length is appropriate. The $k+1$ layer network can be obtained through the k times of division. The output of each sub-sequence is merged into a new sequence as the input of the next layer.

$$h_t^1 = \text{BiLSTM}^0(\text{mess}_{(t-l_0+1) \sim t}^0) \quad (6)$$

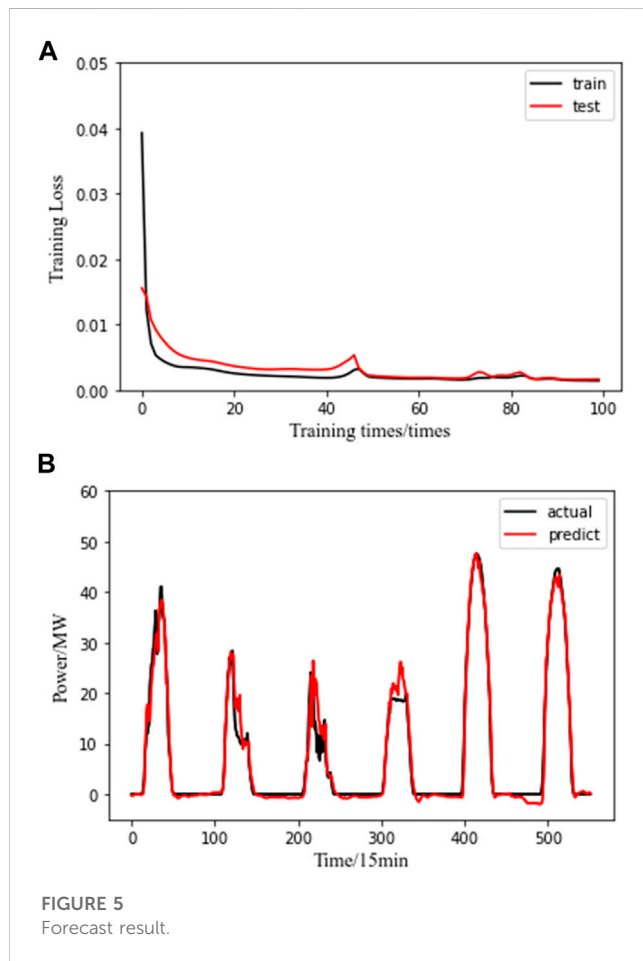
$$h_t^{p+1} = \text{BiLSTM}^p(h_{t-l_p}^p \sim h_t^p) \quad (7)$$

In [Formula 6, 7](#), BiLSTM^p represents the circulation unit of the p layer, mess represents the minimum sub-sequence of layer 0, h_t^p represents t hidden states on layer p , l_p is the minimum sequence length of layer P . The status of layer K is as follows,

$$F = \text{BiLSTM}^P(h_{t-l_k}^P \sim h_t^P) \quad (8)$$

TABLE 1 Date set information.

Month	Number of training samples	Number of test samples	Sampling time
Jan	2476	500	1/1/0:00-1/31/23:45
Apr	2380	500	4/1/0:00-4/30/23:45
Jul	2476	500	7/1/0:00-7/31/23:45
Oct	2476	500	10/1/0:00-10/31/23:45

FIGURE 5
Forecast result.

Taking 2048 input sequences as an example, the sequences are divided into eight sub-sequences twice in total by the presented sliced recurrent network (shown as Figure 3), and the minimum sequence length is 32. Compared with the standard RNN structure, SBiLSTM network can largely reduce the training time. For a network with $k+1$ layers, the training time formula is as follows,

$$t_{SBiLSTM} = \left(nk + \frac{T}{n^k} \right) r \quad (9)$$

In Formula 9, r represents the time spent in each cycle unit, T represents the length of the input sequence, n represents the number of divisions, and K represents the number of divisions. The standard RNN network training time is as follows (10),

$$t_{RNN} = Tr \quad (10)$$

The superiority on speed of SBiLSTM network over RNN network can be expressed by Formula 11,

$$\alpha = \frac{t_{SBiLSTM}}{t_{RNN}} = \frac{1}{n^k} + \frac{nk}{T} \quad (11)$$

3 Model structure and training process

In Figure 4, the model structure is divided into three parts. Part A normalizes the PV Plant data collection and divides it into the training set and the testing set. Part B makes use of the attention mechanism, which can reasonably assign the weights of the training set and the test set, adaptively arrange bigger weights to the important influence factors and suppress the weight of unimportant factors. At the same time, the weight matrix W is updated by iteration. Through the automatic adjusting, the information significantly related to the prediction output is allocated big weight and the accuracy of the prediction is improved. Part C is a sliced bidirectional recurrent neural network. In the figure, B represents BiLSTM. The network construction also includes setting the number of hidden layers, training times, adjusting the learning rate, setting the number of divisions N and division times K of the input sequence. The predicted generation power is the output after the training.

The inputs of the prediction model are climate data and historical power generation data, including historical power data, total irradiance, normal direct irradiance, horizontal scattering irradiance, air temperature, air pressure and relative humidity. Similarly, according to the empirical formula and experimental experience, the number of hidden layer nodes of the prediction model is set to 100, the number of iterations is set to 100, and the input sequence is divided twice, each time divide into eight sub-sequences, with a minimum sequence length of 32. An ultra short term power prediction of 15 min after the current moment is obtained by using the historical data 6 h before the prediction. The main processes include data preprocessing, training model and model analysis. The specific steps as follows.

- (1) 96 historical photovoltaic data and six historical weather data are used as the input sequence.
- (2) The experimental data were normalized.
- (3) The prediction model is established. Initialize the network parameters. Using adam optimization algorithm to adjust the learning rate and the number of iterations.

TABLE 2 Summary of error evaluation indicators.

Model	Error indicator	Jan	Apr	Jul	Oct	Time s)
SBiLSTM-Attention	RMSE	2.439	2.487	1.999	1.192	138.28
	MAE	1.150	1.304	1.159	0.744	
BiLSTM	RMSE	2.498	2.828	2.106	1.443	1004.97
	MAE	1.277	1.631	1.234	1.155	
LSTM-Attention	RMSE	2.641	4.207	2.342	2.007	686.02
	MAE	1.264	2.463	1.581	1.349	
LSTM	RMSE	2.508	3.142	2.227	1.797	568.53
	MAE	1.523	1.736	1.177	1.251	
CNN	RMSE	2.986	3.746	3.542	2.383	2108.64
	MAE	1.955	2.838	2.502	1.703	
MLP	RMSE	3.748	3.972	4.006	3.257	257.83
	MAE	2.745	2.849	2.386	2.157	

- (4) To meet the dimensional requirement of SBiLSTM attention network for input data, the input data is cut.
- (5) Selecting 1 month's historical data as the sample data set, January, July and October include 2976 data sets, and April includes 2880 data sets. In the sample data-set, 500 data are selected as the test set and the rest as the training set.
- (6) Compare and analyze the results predicted by the presented model with other models.

4 Examples and analysis

4.1 Data acquisition and processing

The data set used in this paper is provided by the National Institute of Standards and Technology (NIST). The data sampling time is shown in Table 1. The sampling interval is 15 min, and there are 96 data points every day. The required meteorological data are provided by various equipment in the photovoltaic system. The historical data group includes weather data such as power generation data, air temperature, air pressure, relative humidity, total radiance, normal direct irradiance and horizontal scattering irradiance.

The data selected in the actual prediction includes historical power generation data and meteorological data. Their units are different and the magnitude is quite different. Because of the characteristics of neurons, the activation function mostly limits the output to [0,1], and the power generation is far greater than this range. In order to reduce the influence of neuron saturation caused by the difference of number size between them, the data is normalized, and the input and the target are limited between [0,1]. The normalization formula is shown in Formula 12,

$$P_n = \frac{\rho_n - \rho_{\min}}{\rho_{\max} - \rho_{\min}} \quad (12)$$

In Formula 12, ρ_n is the original data; $\rho_{\min}$ and $\rho_{\max}$ are the minimum and maximum values in the data; P_n is the normalized data.

4.2 Evaluation parameters of prediction model

In this paper, the root mean square error (RMSE) is adopted to evaluate the effect of the model, and the formula is shown in (13).

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (p_f^i - p_t^i)^2}{n}} \quad (13)$$

In (13), n is the total amount of data; p_f^i is the predicted value; p_t^i is the actual value.

At the same time, the error is also calculated by mean absolute error (MAE) through training, shown in Formula 14. The gradient of error is tracked through the training and testing till it reaches the setting value.

$$MAE = \frac{1}{n} = \sum_{i=1}^n |(p_f^i - p_t^i)| \quad (14)$$

4.3 Analysis of prediction results

Figure 5A shows the comparison of the training loss between the training set and the test set in July. It is obvious from the view of the figure that the two curves are very close when the training times achieve 100, and the training loss of the test set is very low (In Figure 5A, the RMSE value of this model is 1.999 and the MAE value is 1.159.), which indicates that the parameters obtained from the training are very suitable for predicting. Figure 5B is the 15-minutues prediction results, it shows that the prediction curve fits the actual power output generation curve well.

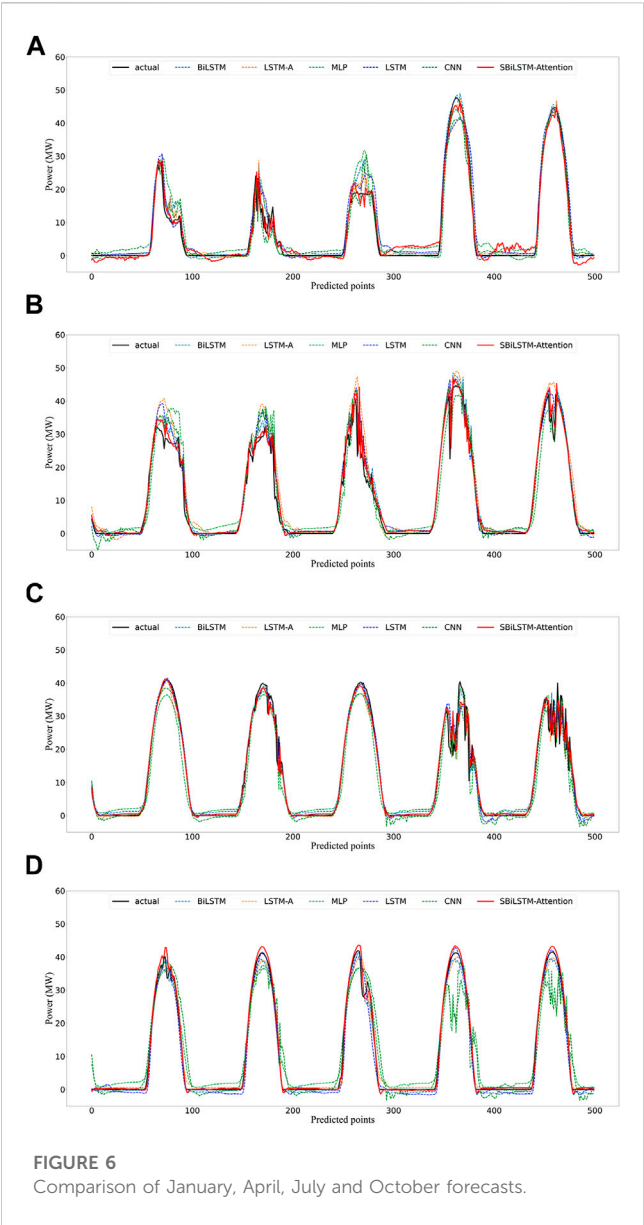


Table 2 lists the comparison of errors predicted by different network models in different months and the total training time. The prediction effect can be seen intuitively from the table. For ultra short-term prediction, the SBiLSTM attention network model has the smallest prediction error value, followed by the BiLSTM neural network model. The prediction result of the basic CNN network model and MLP network model is very general. The prediction result of the LSTM model with only attention mechanism is far worse than that of the LSTM model with attention mechanism and Bi-direction, which shows that the Bi-direction benefits in optimizing the algorithm and improving the accuracy of the prediction model. The prediction effects of six network models are also compared. The performance of the SBiLSTM attention model proposed in this paper is the best, and the training time of the SBiLSTM attention network model is 13.76% of that of the BiLSTM network model, which shows the effectiveness of the slicing.

TABLE 3 Comparison diagram of 5-day error model.

Date	Sunlight	Generated output	RMSE	MAE
26	65	1152.06	0.516	0.403
27	76	1293.92	0.592	0.348
28	96	1903.63	0.583	0.326
29	100	1945.43	0.555	0.352
30	122	2186.02	1.322	1.205

Figure 6 lists the final power predictions of different network models in 4 months (January, April, July and October). It can be clearly seen from the figure that the photovoltaic power generation power prediction curve has a certain periodicity, because the light intensity at night is zero, the output of the photovoltaic array is zero, and in the daytime, the power generation of the photovoltaic array will increase with the increase of the light intensity. Among the six models, SBiLSTM Attention network model has the best prediction effect. In addition, the error value of different months fluctuates greatly, and the prediction error of all models in October is the smallest. This is because the sample data collected in different months are different, and the weather conditions are also different, resulting in a large fluctuation of the error value predicted in different months.

Comparing the power prediction comparison of different months by Table 2, the error of July and October is smaller than that of January and April, and their predicted waveform shapes have little difference. However, the wave forms of January and April fluctuate greatly, which indicates that the light intensity of the forecast day in January and April changes greatly. The change of light intensity in July and October is relatively small, thus the daily generating power is relatively stable. The prediction errors based on SBiLSTM attention network model from April 26 to April 30 are listed below. See Table 3 below.

On the 28th and 29th, it was cloudy. On the 26th and 27th, the light intensity was weak for light rain weather, and the change of light intensity was small. On the 30th, it was cloudy, and the light intensity was relatively large. However, at noon, affected by clouds and strong winds, the change of light intensity was relatively large. It can be clearly seen from Table 3 that the prediction error on the 30th day is obviously large, which is due to the relatively large change of the sunlight intensity, and the change in sunlight intensity from the 26th to the 29th day is small. Therefore, the SBiLSTM attention network model is very suitable for predicting the weather with stable climate and small change in light intensity throughout the day. However, even if the weather conditions fluctuate greatly, the prediction error is relatively small.

5 Conclusion

The SBiLSTM-Attention network model presented in this paper applies the slicing idea to the photovoltaic power prediction. Slicing the cyclic neural network shortens the

training time and improves the prediction efficiency. The prediction model considers multiple meteorological factors, fully considers and optimizes the over fitting problem brought by neural network, and uses Adam optimization algorithm to adjust the learning rate and iteration times to obtain the best prediction model. The application of attention mechanism and bidirectional mechanism into LSTM can fully adaptive assign weight to the impact factors which improves the prediction accuracy, reduces the dimension of data and optimize the algorithm. Testing results show that the prediction accuracy is high, and the RMSE and MAE is 1.999 and 1.159 respectively, the training time is 24.32% of that of LSTM network and 13.76% of that of BILSTM network. It is not affected by weather fluctuations, even in severe weather and climate fluctuations, the prediction error is relatively small, and the accuracy rate is very high in stable weather.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

WC and DL contributed to the development and design of the model. JL implemented the programming of the proposed model algorithm. JY collected experimental data. KZ designed the experiment to prove the superiority of the proposed method. All

authors wrote parts of the manuscript. All authors have read and agreed to the submission of the manuscript.

Funding

The research is supported by the Science and Technology Project of State Grid Shanxi Electric Power Co., LTD., China (No. SGSXJC00YCJS2100679).

Conflict of interest

WG, JL, JY, and KZ were employed by the company State Grid Jincheng Power Supply Company.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process and
Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 20 February 2023

ACCEPTED 20 March 2023

PUBLISHED 04 April 2023

CITATION

Wang S and Yang J (2023), Active
disturbance rejection control of three-
phase LCL power conversion system
under non-ideal grid conditions.
Front. Energy Res. 11:1170058.
doi: 10.3389/fenrg.2023.1170058

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Active disturbance rejection control of three-phase LCL power conversion system under non-ideal grid conditions

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Under non-ideal grid operating conditions such as unbalanced grid voltage and harmonic grid that are commonly found in microgrid conditions, the negative sequence components of the microgrid voltage interfere with the active and reactive current controls in the power conversion system, leading to an increase in the harmonic content of the grid-side current and affecting the power quality of the microgrid system. To solve these problems, firstly, the mathematical model of the LCL-type power conversion system is analyzed, and a linear active disturbance rejection control based on model compensation is designed. Secondly, the influence of non-ideal power grid conditions on the control of the LCL-type power conversion system is analyzed, and the active disturbance rejection control strategy of the LCL-type power conversion system based on frequency-locked loops with harmonic cancellation modules (HCM-FLL) is proposed, which speeds up the system, improves the system's robustness, and reduces the harmonic content of the network measurement current under the condition of power grid voltage unbalance and harmonic power grid. Finally, by using the verification of MATLAB/Simulink simulation, the current power quality obviously under the condition of voltage unbalance and harmonic power grid is evidently improved by the proposed control strategy. When compared to the traditional control methods, the control strategy proposed in this study features a simple control structure, making it easy to implement in engineering without requiring high controller performance or additional circuits. This reduces design costs and provides a wide range of controller parameters, ensuring strong anti-interference performance without the need for frequent controller parameter adjustments.

KEYWORDS

microgrid system, non-ideal grid, LCL-type power conversion system, LADRC, DSOGI-FLL

1 Introduction

The microgrid system realizes the efficient utilization and flexible control of distributed energy resources. As an important subsystem of the microgrid system, the energy storage system provides continuous and reliable power supply for the load in the microgrid system and ensures good power quality (Che et al., 2015; Xin et al., 2015; Wu et al., 2019). The LCL-type power conversion system (LCL-type PCS) is becoming more and more popular in the construction of the microgrid due to its effective filtering and small size.

Under ideal grid conditions, the control of the LCL-type PCS is relatively mature, and the output power quality can be significantly improved by adjusting the PI parameters (Gao

et al., 2021) or improving the current controller (Errouissi and Al-Durra, 2018) by reasonable methods. However, in the actual operation, the microgrid often has non-ideal phenomena such as grid voltage unbalance and harmonic pollution. If the traditional vector control is adopted, the PCS output current will have serious unbalance and harmonic distortion, while the output active power and reactive power will also fluctuate, which will further pollute the microgrid and reduce the reliability of the operation of the microgrid system. Therefore, it is necessary to study the high-performance control strategy of the PCS under non-ideal power grids.

Li et al. (2021) adopted the traditional PI controller, using the positive- and negative-sequence rotating coordinate system (frame) and multiple filters to separate the positive and negative components for separate control, so as to suppress the influence of the non-ideal power grid on the inverter. The method is easy to implement, a mature technology that is widely used in engineering, but its control structure is complex, the amount of calculation is large, and it is easy to cause deterioration of the dynamic performance of the system. Jin et al. (2016) studied the model predictive control strategy of a three-phase three-level neutral point clamped (NPC) grid-connected inverter under unbalanced power grid, which improves the dynamic performance of the system. Li Z. et al. (2020) proposed a deadbeat predictive power control (DPPC) based on fuzzy PI composite controller and power prediction corrector, which realizes the stable control of a PWM rectifier under grid unbalance. The scheme proposed in Jin et al. (2016) and Li Z. et al. (2020) can achieve better control effects under the non-ideal power grid, but the controller designed by these two methods has a large amount of computation during the operation, which requires high hardware computing power that increases the system design cost. Xiong et al. (2021) proposed a strategy based on the frequency trajectory planning to improve the frequency stability of the inverter droop control in non-ideal power grids, but it is less robust to voltage-amplitude transformation and harmonic distortion. Ma et al. (2020) proposed an LCL-type grid-connected inverter control scheme based on the active disturbance rejection control and proposed a system parameter design method based on root locus analysis, which improves the stability of the grid-connected inverter under high-inductive anti-grid conditions but lacks the analysis of voltage unbalance and harmonic distortion. Li S. et al. (2020) proposed a linear/non-linear active disturbance rejection switching control phase lock loop and its pre-synchronous control strategy for virtual synchronous generator grid-connected control technology, which achieves good grid-connected effects under non-ideal conditions such as grid unbalance and frequency and phase transition, but the control structure is complex, the setting parameters are large, and the engineering implementation is difficult.

In addition, under non-ideal power grids, if the phase-locked loop cannot eliminate the harmonic interference of the power grid, it will cause the PCS to run out of sync, and in severe cases, it will even lead to system shock instability. Therefore, the influence of non-ideal power grids on phase-locked loops have to be considered simultaneously when designing control strategies. Pan et al. (2019) proposed a new type of phase-locked loop, which improves an improved-dual adaptive notch filter (IDANF) and multivariable filter (MVF), which can well eliminate the negative sequence components and fundamental frequency oscillations in non-ideal

power grids, but the proposed phase-locked loop structure is complex and difficult to design. Shi et al. (2021) proposed a fixed-length transfer delay-based adaptive frequency-locked loop (TD-AFLL) to improve the detection accuracy of phase angle and amplitude under power grid distortion, but the phase-locked loop is computationally intensive and requires high hardware computing power. Din et al. (2020) described an improved phase-locked loop structure that ensures high phase margin and reduces the likelihood of resonant frequency in DFIG systems under weak grids. However, the phase-locked loop of this structure is less resistant to grid voltage unbalance and harmonic distortion. Liu et al. (2022b) improved the conventional synchronous reference frame (SRF)-PLL, which solves the problem of the large attenuation of DC components introduced by loads and grid disturbances in high-inductance and high-voltage transmission systems that causes the performance of PLL to degrade during transients but lacks the analysis of grid disturbances during steady-state periods. Liu et al. (2022a) proposed a robust real-time algorithm that can quickly separate the positive sequence component (PSC) from multiple decaying DC (DDC) components, DC bias component, negative-sequence component, and harmonics. This approach ensures a unit grid cycle response time while suppressing many types of interference. However, the disadvantage is that the algorithm has a complex structure and is difficult to design and set parameters.

Although there are many studies on PCS control strategies under non-ideal power grids, most of the control strategies are still very difficult in engineering applications because there are many interference factors in non-ideal power grids, and most of the related research can only propose solutions for some of them, and often the control structure is complex, the calculation amount is redundant, and the controller performance requirements are high. In order to overcome the above technical challenges, this article analyzes the influence of positive- and negative-sequence components of grid voltage on PCS current control under non-ideal grid conditions by establishing a three-phase LCL-type PCS mathematical model, a control strategy based on improved linear active disturbance rejection control (LADRC), and frequency-locked loop with harmonic cancellation module (HCM-FLL). When compared with the conventional control strategies, the control strategy proposed in this paper has the following advantages:

- (1) The proposed control strategy combines the characteristics of LADRC with simple structure, easy implementation, and strong applicability. LADRC is introduced to improve the PCS current controller, and the active and reactive currents of the PCS are effectively controlled by using the LADRC immunity compensation idea to improve the immunity performance of the controller and enhance the robustness of the system.
- (2) HCM-FLL eliminates low-frequency harmonics in harmonic grids through the pre-harmonic cancellation module and improves the frequency and phase information acquisition accuracy in harmonic power grids. At the same time, the positive- and negative-sequence calculator is used to eliminate the interaction of positive and negative components in the unbalanced power grid by controlling the positive- and negative-sequence components, respectively, and then eliminating the influence of the coupling of positive- and negative-sequence components on the output power.

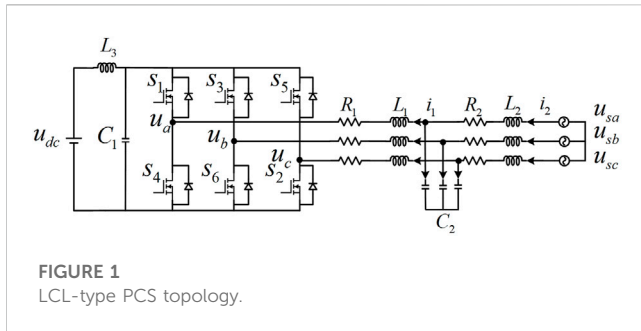


FIGURE 1
LCL-type PCS topology.

2 Mathematical model of power conversion system for microgrid

The topological structure of the LCL-type PCS studied in this article is shown in Figure 1. The LCL-type PCS adopts a unipolar transformation topology. $S_1 - S_6$ are six switching devices of the three-phase inverter. R_1 and R_2 are equivalent internal resistances of filter inductors L_1 and L_2 , respectively. L_1 , L_2 , and C_2 constitute the LCL filters of the PCS. L_3 is the DC filter inductance and C_1 is the DC filter capacitor.

The inductance currents i_{1a} , i_{1b} , and i_{1c} ; grid-connected currents i_{2a} , i_{2b} , and i_{2c} ; capacitor voltages u_{ca} , u_{cb} , and u_{cc} ; and inverter grid-connected voltages u_{sa} , u_{sb} , and u_{sc} are selected as the state variables, and the state equation in the dq coordinate system is obtained through coordinate transformation, as shown in Eq. 1:

$$\begin{cases} \frac{di_{1d}}{dt} = -\frac{R_1}{L_1}i_{1d} + \omega i_{1q} - \frac{1}{L_1}u_{cd} + \frac{1}{L_1}u_d \\ \frac{di_{1q}}{dt} = -\frac{R_1}{L_1}i_{1q} - \omega i_{1d} - \frac{1}{L_1}u_{cq} + \frac{1}{L_1}u_q \\ \frac{di_{2d}}{dt} = -\frac{R_2}{L_2}i_{2d} + \omega i_{2q} - \frac{1}{L_2}u_{cd} + \frac{1}{L_2}u_{sd} \\ \frac{di_{2q}}{dt} = -\frac{R_2}{L_2}i_{2q} - \omega i_{2d} - \frac{1}{L_2}u_{cq} + \frac{1}{L_2}u_{sq} \\ \frac{du_{cd}}{dt} = \frac{1}{C_2}i_{1d} - \frac{1}{C_2}i_{2d} + \omega u_{cq} \\ \frac{du_{cq}}{dt} = \frac{1}{C_2}i_{2d} - \frac{1}{C_2}i_{1d} - \omega u_{cd} \end{cases} \quad (1)$$

where i_{1d} and i_{1q} are the inductive current vector dq -axis components; i_{2d} and i_{2q} are the grid-connected current dq -axis components; u_{cd} and u_{cq} are the voltage dq -axis components; u_{sd} and u_{sq} are grid-connected voltage dq -axis components; and u_d and u_q are the AC bus voltage dq -axis components. ω is the AC bus voltage fundamental angular frequency of the microgrid.

It can be seen from Eq. 1 that the LCL-type PCS is a high-order, non-linear, strongly coupled, multivariable system with resonance characteristics. The quality of the incoming current will be affected if the controller is not decoupled and the resonance suppression strategy is not adopted properly. At present, the common decoupling and resonance suppression strategies have to obtain more parameters in the system. In practical engineering, multiple sensors are required to obtain the values of each variable, which increases the design cost.

Meanwhile, affected by temperature, humidity, and service time, the PCS parameters change, thus affecting the actual control effect.

In an ideal power grid, reasonable designing of decoupling and resonance suppression strategies can control the LCL-type PCS well. In a non-ideal power grid, the positive- and negative-sequence components of the power grid will cause output power fluctuation and affect the PCS control effect.

When the three-phase power grid voltage is unbalanced according to the symmetric component method (Shigenobu et al., 2020), power grid voltage can be expressed as

$$\begin{bmatrix} u_{sa} \\ u_{sb} \\ u_{sc} \end{bmatrix} = V_s^+ \begin{bmatrix} \cos(\omega t + \varphi^+) \\ \cos(\omega t + \varphi^+ - 120^\circ) \\ \cos(\omega t + \varphi^+ + 120^\circ) \end{bmatrix} + V_s^- \begin{bmatrix} \cos(-\omega t + \varphi^-) \\ \cos(-\omega t + \varphi^- - 120^\circ) \\ \cos(-\omega t + \varphi^- + 120^\circ) \end{bmatrix}, \quad (2)$$

where V_s^+ and V_s^- are the amplitudes of the positive and negative fundamental components, respectively; φ^+ and φ^- are the phases of the positive and negative fundamental components, respectively; and θ is the phase angle of the grid voltage. The coordinate transformation of Eq. 2 yields the expression of the grid voltage in the dq coordinate system.

$$\begin{bmatrix} u_{gd+1} \\ u_{gq+1} \end{bmatrix} = V_s^+ \begin{bmatrix} \cos(\omega t + \varphi^+ - \theta) \\ \sin(\omega t + \varphi^+ - \theta) \end{bmatrix} + V_s^- \begin{bmatrix} \cos(-\omega t + \varphi^- - \theta) \\ \sin(-\omega t + \varphi^- - \theta) \end{bmatrix}, \quad (3)$$

$$\begin{bmatrix} u_{gd-1} \\ u_{gq-1} \end{bmatrix} = V_s^+ \begin{bmatrix} \cos(\omega t + \varphi^+ + \theta) \\ \sin(\omega t + \varphi^+ + \theta) \end{bmatrix} + V_s^- \begin{bmatrix} \cos(-\omega t + \varphi^- + \theta) \\ \sin(-\omega t + \varphi^- + \theta) \end{bmatrix}. \quad (4)$$

Using voltage and current components in the dq coordinate system, the expression of instantaneous power on the grid side can be obtained

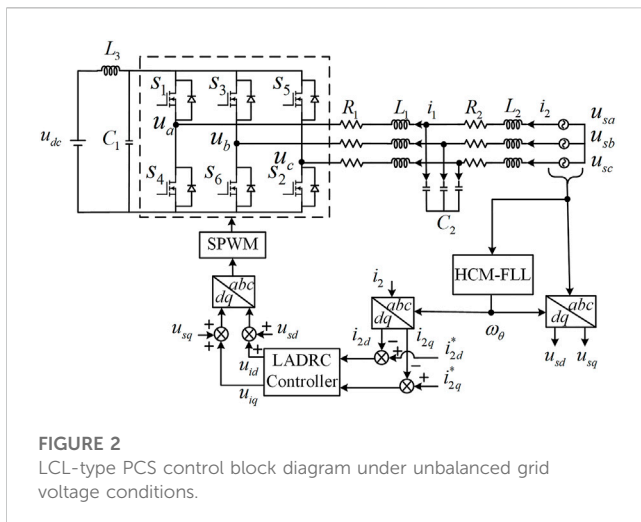
$$\begin{cases} p(t) = p_0 + p_{c2} \cos(2\omega t) + p_{s2} \sin(2\omega t) \\ q(t) = q_0 + q_{c2} \cos(2\omega t) + q_{s2} \sin(2\omega t), \end{cases} \quad (5)$$

where p_0 is the average value of the instantaneous active power and q_0 is the average value of the instantaneous reactive power. p_{c2} , p_{s2} , q_{c2} , and q_{s2} are the second harmonic power amplitudes. The amplitude of these powers can be expressed as

$$\begin{bmatrix} p_0 \\ p_{c2} \\ p_{s2} \\ q_0 \\ q_{c2} \\ q_{s2} \end{bmatrix} = \frac{3}{2} \begin{bmatrix} u_{gd}^+ & u_{gq}^+ & u_{gd}^- & u_{gq}^- \\ u_{gd}^- & u_{gq}^- & u_{gd}^+ & u_{gq}^+ \\ u_{gd}^+ & -u_{gq}^+ & -u_{gd}^- & u_{gq}^- \\ u_{gd}^- & -u_{gq}^- & u_{gd}^+ & -u_{gq}^+ \\ u_{gd}^- & -u_{gq}^- & u_{gd}^+ & -u_{gq}^+ \\ -u_{gd}^- & -u_{gq}^- & u_{gd}^+ & u_{gq}^+ \end{bmatrix} \begin{bmatrix} i_{gd}^+ \\ i_{gq}^+ \\ i_{gd}^- \\ i_{gq}^- \end{bmatrix}, \quad (6)$$

where u_{gd}^+ , u_{gq}^+ , u_{gd}^- , and u_{gq}^- are the positive- and negative-sequence components of the voltage, respectively. i_{gd}^+ , i_{gq}^+ , i_{gd}^- , and i_{gq}^- are the positive- and negative-sequence components of the current, respectively. According to Formula 6, the instantaneous active and reactive powers in the three-phase unbalanced power grid will fluctuate, and the converter will output the grid-connected current with high harmonics (Wang et al., 2020).

In view of the above problems, the LCL-type PCS requires a control strategy with decoupling and damping effects that is easy to be applied in engineering in a non-ideal power grid environment.

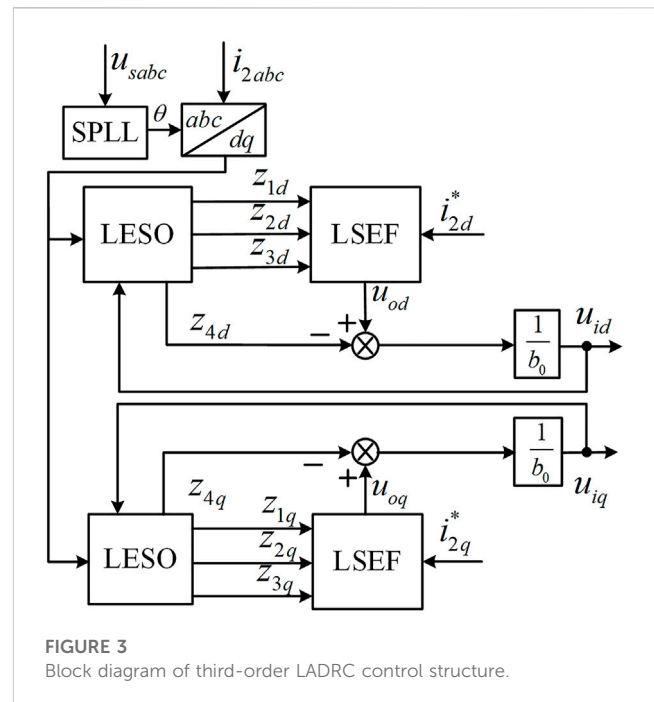


3 LCL-type PCS control strategy under non-ideal power grid condition

In view of the problems of the LCL-type PCS proposed in Section 1 under the condition of power grid voltage unbalance, an active disturbance rejection control strategy based on an improved DSOGI-FLL was proposed, as shown in Figure 2. In this article, the DSOGI-FLL with harmonic elimination function is proposed to accurately obtain the grid voltage phase under non-ideal conditions, and the current component in the coordinate system is obtained through coordinate transformation. The given current and sampled current are passed through a third-order LADRC current controller, which is then added to the voltage component. After the coordinate transformation, a drive signal is obtained through SPWM modulation to control the action of the power switching device and realize system control.

3.1 Current controller based on third-order LADRC

The basic idea of active disturbance rejection control (ADRC) is to compensate the non-linear uncertain objects with unknown interference into integrator series-type through non-linear state feedback and combine the control rate into the ideal controller through non-linear state feedback (Chang et al., 2014). Since an extended state variable is designed by using an extended state observer (LESO) to track the un-modeled and inaccurate parts of the model, as well as the disturbance and coupling parts of the model caused by external environment changes, and observe and compensate them in real time, the ADRC has the characteristics of strong robustness and anti-interference ability. However, the traditional ADRC has many parameters to adjust, and the non-linear function is difficult to determine and popularize. In order to simplify parameter settings for engineering applications, Gao (2006) proposed the linear active disturbance rejection control (LADRC), which greatly reduces the parameters that have to be adjusted and promotes the development and application of the active disturbance rejection control.



The LCL-type PCS is a high-order, non-linear, strongly coupled multivariable system with resonance characteristics. There are three coupling channels between the active current control axis and reactive current control axis in the dq coordinate system, which cannot realize independent control of the two axes. The traditional modeling-dependent current loop control method, whether in decoupling or in resonance suppression, has a high degree of dependence on the model and a complex controller design. In this article, the LADRC technique is introduced to treat all the factors that make the system output deviate from a given value as “total disturbances,” and estimates using the linear extended state observer (LESO), and finally, implements feed-forward compensation. The “total disturbances” include external disturbances and internal disturbances, and the external disturbances mainly refer to the environmental disturbances caused by the non-ideal grid such as grid voltage distortion, harmonic grid, and the disturbances caused by the changes in PCS system parameters, whereas the internal disturbances refer to the coupling disturbances between the dq axes, LCL resonance disturbances, and the disturbances caused by inaccurate modeling. This method provides a better decoupling performance while simplifying the design and also has a strong suppression effect on resonance, providing better parameter robustness for the system.

The order of LADRC can be judged by the number of integrators that pass through the “shortest” path from input to output of the system block diagram of the controlled object (Han, 2007). The order of the LCL-type PCS is 3, therefore it is necessary to design a third-order LADRC controller. The LADRC control structure diagram of the LCL-type PCS is shown in Figure 3.

In Figure 3, the definition of the main circuit variable is the same as that provided in Figure 1. The fundamental wave angular frequency ω and the phase θ of the AC bus voltage in the common coupling point microgrid are provided by DSOGI-FLL for participating in the dq

coordinate transformation. The active power and reactive power exchanged between the PCS and microgrid system are determined by the current reference value i_{2d}^* of the d-axis current value and the current reference value i_{2q}^* of the q-axis current value, respectively. $z_{1d} \sim z_{4d}$ and $z_{1q} \sim z_{4q}$ represent the observed quantities of the LESO in the d-axis current and q-axis current LADRC controllers, respectively.

The dynamic characteristics of the grid current i_{2d} in the rotating coordinate system can be expressed by the third-order differential equation shown in Eq. 7:

$$\begin{cases} \frac{d^{(3)}i_{2d}}{dt} = b_0 u_{id} + f_d \begin{pmatrix} u_{sd}, u_{sq}, i_{2d}, i_{2q}, \Delta L_1, \\ \Delta C_2, \Delta L_2, \omega, R_1, R_2 \end{pmatrix} \\ \frac{d^{(3)}i_{2q}}{dt} = b_0 u_{iq} + f_q \begin{pmatrix} u_{sd}, u_{sq}, i_{2d}, i_{2q}, \Delta L_1, \\ \Delta C_2, \Delta L_2, \omega, R_1, R_2 \end{pmatrix} \end{cases} \quad (7)$$

where $b_0 = 1/L_1 L_2 C_2$, and functions f_d and f_q represent the total perturbation on the d-axis and q-axis current values, respectively.

LADRC mainly includes LESO and linear state error feedback (LSEF), and their design methods are explained in the following section.

3.1.1 Design of LESO

LESO in the third-order LARC belonging to the higher-order LESO, which has a significantly enhanced disturbance suppression ability in the low-frequency band and is conducive to better the tracking system state and interference. In the middle-frequency band, the peak value of the amplitude-frequency curve of the higher-order LESO increases, and the step response produces a large overshoot or even oscillation, which is not conducive to the stability of the system. As the gain of high frequency increases, the suppression ability of high-frequency noise is significantly weakened (Zhang et al., 2015). To solve this problem, a model compensation method was proposed to introduce the resonance information ω_{res} in the LCL-type PCS model into the LESO equation. By improving the LESO structure, the resonance information is not included in the “total disturbance” to be estimated by LESO, such that the amplitude of the “total disturbance” to be estimated by LESO is reduced and the convergence speed and observation accuracy of LESO is improved, as well as the performance of the controller are improved.

The “total disturbance” represented by f_d and f_q is denoted as $f_d = f_{wd} + f_{0d}$ and $f_q = f_{wq} + f_{0q}$, respectively, where f_{wd} and f_{wq} represent the known disturbances containing the model information ω_{res} and, f_{0d} and f_{0q} represent the disturbances of the unknown part of the “total disturbance,” therefore Eq. 7 can be rewritten as

$$\begin{cases} \frac{d^{(3)}i_{2d}}{dt} = b_0 u_{id} + f_{wd} + f_{0d} = b_0 u_{id} - \omega_{res}^2 \frac{di_{2d}}{dt} + f_{0d} \\ \frac{d^{(3)}i_{2q}}{dt} = b_0 u_{iq} + f_{wq} + f_{0q} = b_0 u_{iq} - \omega_{res}^2 \frac{di_{2q}}{dt} + f_{0d}. \end{cases} \quad (8)$$

The LESO design method is the same for the d-axis and q-axis current values. Taking the d-axis current value as an example, the d-axis current differential equation in Eq. 8 is written in the form of a state-space expression.

$$\begin{cases} \dot{x} = Ax + Bu_{id} + Eh \\ y = Cx. \end{cases} \quad (9)$$

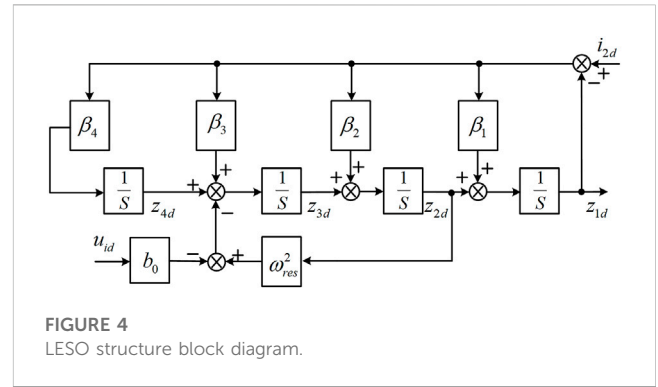


FIGURE 4
LESO structure block diagram.

In the formula $x = [x_1 \ x_2 \ x_3 \ x_4]^T$, $x_1 = i_{2d}$, $x_2 = \dot{x}_1$, and $x_3 = \dot{x}_2$, $x_4 = f_{0d}$ is the expansion state variable. $h = \dot{f}_{0d}$ is the output of the d-axis current active disturbance rejection controller, and each coefficient matrix is

$$\begin{cases} A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & -\omega_{res}^2 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} 0 \\ 0 \\ b_0 \\ 0 \end{bmatrix}, E = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \\ C = [1 \ 0 \ 0 \ 0] \end{cases} \quad (10)$$

According to the design idea of LADRC, LESO can be established as

$$\begin{cases} \dot{z} = Az + Bu_{id} + L(y - \hat{y}) \\ \hat{y} = Cz \end{cases} \quad (11)$$

where $z = [z_{1d} \ z_{2d} \ z_{3d} \ z_{4d}]^T$ is the observed quantity of LESO, $L = [\beta_1 \ \beta_2 \ \beta_3 \ \beta_4]^T$ is the gain matrix of LESO, and $\hat{y} = z_{1d}$ is the output of LESO.

To sum up, the structural block diagram of LESO is drawn as shown in Figure 4.

The observation error of LESO can be obtained by subtracting Eq. 11 from Eq. 9, which can be written as

$$\begin{aligned} \dot{e}_d &= A_e e_d + E h \\ e_d &= [x_1 - z_1 \ x_2 - z_2 \ x_3 - z_3 \ x_4 - z_4] \\ A_e &= A - LC = \begin{bmatrix} -\beta_1 & 1 & 0 & 0 \\ -\beta_2 & 0 & 1 & 0 \\ -\beta_3 & -\omega_{res}^2 & 0 & 1 \\ -\beta_4 & 0 & 0 & 0 \end{bmatrix} \end{aligned} \quad (12)$$

According to Eq. 12, the characteristic equation is

$$\begin{aligned} D(\lambda) &= |\lambda I - (A - LC)| \\ &= \lambda^4 + \beta_1 \lambda^3 + (\beta_2 + \omega_{res}^2) \lambda^2 + (\beta_1 \omega_{res}^2 + \beta_3) \lambda + \beta_4. \end{aligned} \quad (13)$$

According to the modern control theory, when all characteristic roots have negative real parts, the initial bias of the observer will decay exponentially, and the decay rate depends on the position of the observer pole. The farther the imaginary axis, the faster will be the decay rate. In order to facilitate implementation, all poles of the observer are generally chosen to be the same negative real number, such that LESO converges in a finite period. Observation $z_{1d}, z_{2d}, z_{3d}, z_{4d}$ tends to the state variable x_1, x_2, x_3, x_4 being observed. h represents the derivative of the unknown perturbation in the “total disturbance,” which must be bound.

Therefore, a stable LESO system can be obtained only by determining the appropriate value of $L = [\beta_1 \ \beta_2 \ \beta_3 \ \beta_4]^T$.

According to the abovementioned ideas, all the characteristic roots of the state observer are set as $-\omega_0$, then the characteristic equation can be expressed as

$$D^*(\lambda) = (\lambda + \omega_0)^4 = \lambda^4 + 4\omega_0\lambda^3 + 6\omega_0^2\lambda^2 + 4\omega_0^3\lambda + \omega_0^4. \quad (14)$$

Let $D(\lambda) = D^*(\lambda)$, that is,

$$\begin{aligned} \lambda^4 + 4\omega_0\lambda^3 + 6\omega_0^2\lambda^2 + 4\omega_0^3\lambda + \omega_0^4 \\ = \lambda^4 + \beta_1\lambda^3 + (\beta_2 + \omega_{res}^2)\lambda^2 + (\beta_1\omega_{res}^2 + \beta_3)\lambda + \beta_4. \end{aligned} \quad (15)$$

Therefore,

$$\begin{cases} \beta_1 = 4\omega_0 \\ \beta_2 = 6\omega_0^2 - \omega_{res}^2 \\ \beta_3 = 4\omega_0^3 - \beta_1\omega_{res}^2 \\ \beta_4 = \omega_0^4. \end{cases} \quad (16)$$

3.1.2 Design of LSEF

For third-order LADRC, the LSEF control rate is designed as follows:

$$u_{0d} = k_p(\dot{i}_{2d}^* - z_{1d}) - k_1 z_{2d} - k_2 z_{3d}, \quad (17)$$

where $\dot{i}_{2d}^*$ is the d-axis current setting value represented in Figure 2. k_p , k_1 , and k_2 are the feedback gains of the LSEF. The control law of the d-axis current active disturbance rejection controller is as follows:

$$u_{id} = \frac{u_{0d} - f_{\omega d} - \hat{f}_{0d}}{b_0} = \frac{u_{0d} - f_{\omega d} - z_{4d}}{b_0}, \quad (18)$$

where $f_{\omega d}$ is part of the disturbance in the “total disturbance” known according to model information and $\hat{f}_{0d}$ is the estimated value of f_{0d} , representing the total disturbance in the unknown part of the “total disturbance” observed by LESO z_{4d} . Ignoring the observation error of LESO, the following equation is obtained:

$$\begin{aligned} \frac{d^{(3)}i_{2d}}{dt} &= u_{0d} - \omega_{res}^2 \frac{di_{2d}}{dt} + (f_d' - \hat{f}_d) \\ &\approx u_{0d} - \omega_{res}^2 \frac{di_{2d}}{dt}. \end{aligned} \quad (19)$$

By substituting Eqs 17, 19, we then use Laplace transform to obtain the transfer function of the system on the d-axis current value as

$$\frac{u_{id}(s)}{i_{2d}^*(s)} = \frac{k_p}{s^3 + k_2 s^2 + (k_1 + \omega_{res}^2)s + k_p}. \quad (20)$$

The characteristic equation is

$$s^3 + k_2 s^2 + (k_1 + \omega_{res}^2)s + k_p = 0. \quad (21)$$

According to the “bandwidth method” proposed by Zhang et al. (2015), the closed-loop pole of the system is located at $-\omega_c$, and the following results are obtained:

$$(s + \omega_c)^3 = s^3 + 3\omega_c s^2 + 3\omega_c^2 s + \omega_c^3. \quad (22)$$

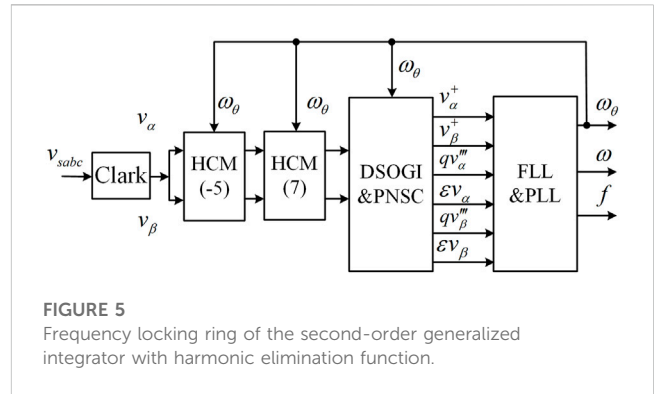


FIGURE 5

Frequency locking ring of the second-order generalized integrator with harmonic elimination function.

Comparing the coefficients of Eqs 20, 21, we get

$$\begin{cases} k_p = \omega_c^3 \\ k_1 = 3\omega_c^2 - \omega_{res}^2 \\ k_2 = 3\omega_c. \end{cases} \quad (23)$$

During the actual designing, it is ensured that the LESO bandwidth ω_0 is greater than the LSEF gain ω_c , i.e., $\omega_0 = 3 \sim 10\omega_c$ to achieve an LESO response speed greater than the control speed of the LSEF.

The design method of the q-axis LSEF is exactly the same as that of the d-axis LSEF, which is designed in the same way.

3.2 HCM-FLL structure and design

The conventional synchronous reference frame PLL (SRF-PLL) has a good response speed under the ideal grid. However, under the non-ideal grid, SRF-PLL will generate large errors in determining the grid voltage frequency and phase information due to harmonics, voltage dips, frequency variations, etc., which will cause errors in synchronizing the converter with the grid and affect the quality of the grid-connected current.

In order to solve this problem, a harmonic cancellation frequency-locked loop is proposed, which is composed of the harmonic cancellation module (HCM), second-order generalized integrator decoupling module (DSOGI-PNSC), and frequency-locked loop and phase-locked loop (FLL + PLL), as shown in Figure 5.

The advantages of this structure are as follows:

- (1) The front harmonic elimination module can effectively eliminate low-frequency harmonics in the harmonic grid and improve the accuracy of frequency and phase information acquisition in the harmonic grid.
- (2) DSOGI-PNSC adopts the second-order generalized integrator quadrature signal generator (SOGI-QSG), and the positive- and negative-sequence fundamental frequency components of the power grid voltage are extracted when the power grid is disturbed and the power grid voltage is unbalanced. The positive-/negative-sequence calculator (PNSC) is used to eliminate the interaction between the positive- and negative-sequence components of the voltage, to achieve the separation of

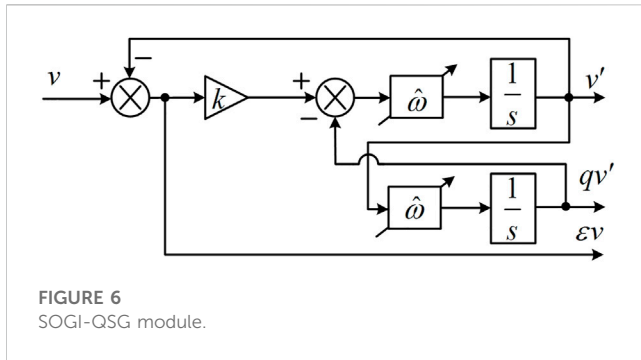


FIGURE 6
SOGI-QSG module.

positive- and negative-sequence components, by controlling the positive- and negative-sequence components, respectively, and to eliminate the influence of positive- and negative-sequence component coupling on the output power.

- (3) The frequency of the adaptive filter in SOGI-QSG is provided by FLL, which depends on frequency feedback and can realize frequency adaptation of the input signal. When compared with PLL, FLL has a better stability than does PLL because the frequency information is more stable than the phase information, and the frequency oscillation is smaller and the smoothness is higher in the dynamic process.

3.2.1 SOGI-QSG module

When the power grid voltage is unbalanced, it is necessary to separate the positive- and negative-sequence components and phase lock the positive-sequence component. The orthogonal signal generator (SOGI-QSG) based on the second-order generalized integrator is shown in Figure 6. By constructing an adaptive filter based on the principle of the internal mode, it can generate signals with a difference of 90° from the input signal to achieve positive and negative sequence separation.

In Figure 6, v is the system input signal, v' is the system output signal, εv is the frequency error signal required by FLL, $\hat{\omega}$ is the resonant angular frequency of the adaptive filter, and $q = e^{-(j\pi/2)}$.

Xu et al. (2021) reported that the second-order generalized integrator has band-pass filter characteristics. The smaller the k value is, the better the filtering performance will be, but the dynamic performance of the system will be affected. In order to ensure both the filtering and dynamic performances, $k = \sqrt{2}$ is selected. At the same time, because of the characteristics of its band-pass filter, when the harmonic content is too high, it cannot filter harmonics well, and so a harmonic cancellation module has to be designed.

3.2.2 Harmonic cancellation module

Considering the power grid voltage unbalance containing the N th harmonics, the power grid voltage after the Clarke transformation can be expressed as

$$\begin{cases} v_{\alpha} = v_{\alpha}^{+} + v_{\alpha}^{-} + v_{\alpha}^n \\ v_{\beta} = v_{\beta}^{+} + v_{\beta}^{-} + v_{\beta}^n \end{cases} \quad (24)$$

where v_{α}^{+} and v_{β}^{+} are positive-sequence fundamental wave components of the power grid voltage, v_{α}^{-} and v_{β}^{-} are negative-

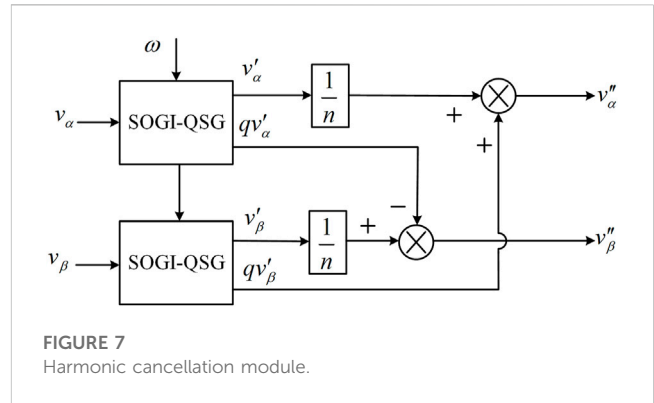


FIGURE 7
Harmonic cancellation module.

sequence fundamental wave components of the power grid voltage, and v_{α}^n and v_{β}^n are the N th harmonic components of the power grid voltage.

When the resonant frequency of SOGI-QSG is equal to the grid voltage frequency, i.e., $\hat{\omega} = \omega$, SOGI-QSG can track the positive- and negative-sequence fundamental components of the grid voltage without static differences and, at the same time, have attenuation and phase shift effects on the N th harmonic, which is as follows:

$$\begin{cases} v'_{\alpha} = v_{\alpha}^{+} + v_{\alpha}^{-} + v_{\alpha}^{*n} \\ qv'_{\alpha} = v_{\beta}^{+} - v_{\beta}^{-} + \frac{1}{n}v_{\beta}^{*n} \end{cases} \quad (25)$$

$$\begin{cases} v'_{\beta} = v_{\beta}^{+} + v_{\beta}^{-} + v_{\beta}^{*n} \\ qv'_{\beta} = -v_{\alpha}^{+} + v_{\alpha}^{-} - \frac{1}{n}v_{\alpha}^{*n} \end{cases} \quad (26)$$

where v'_{α} and v'_{β} are in the phase with the input signals v_{α}^{+} and v_{β}^{+} , and qv'_{α} and qv'_{β} are orthogonal to the input signals v_{α}^{+} and v_{β}^{+} . v_{α}^{*n} and v_{β}^{*n} are the output harmonic components with the same amplitude and with the different phases are v_{α}^n and v_{β}^n .

Eqs 25, 26 show that although both the amplitude and phase of the harmonic components change, the amplitude of the harmonics only changes with the number of harmonics. From the two equations, the N th harmonic term $(1/n)v_{\alpha}^{*n}$ on the α axis can be eliminated by multiplying v'_{α} by the coefficient $(1/n)$ and adding it to qv'_{β} . Similarly, the N th harmonic term $(1/n)v_{\beta}^{*n}$ on the β axis can be eliminated. The voltage in the two-phase stationary coordinate system after harmonic elimination can be expressed as

$$v_{\alpha\beta}' = \begin{bmatrix} v'_{\alpha} & v'_{\beta} \end{bmatrix}^T = \left(\frac{1}{n} - 1\right)v_{\alpha\beta}^{+} + \left(\frac{1}{n} + 1\right)v_{\alpha\beta}^{-} \quad (27)$$

In the formula

$$\begin{cases} v''_{\alpha} = \frac{1}{n}v'_{\alpha} + qv'_{\beta} = \left(\frac{1}{n} - 1\right)v_{\alpha}^{+} + \left(\frac{1}{n} + 1\right)v_{\alpha}^{-} \\ v''_{\beta} = \frac{1}{n}v'_{\beta} - qv'_{\alpha} = \left(\frac{1}{n} - 1\right)v_{\beta}^{+} + \left(\frac{1}{n} + 1\right)v_{\beta}^{-} \end{cases} \quad (28)$$

it can be seen that the two-phase voltage obtained after the transformation eliminates the N th harmonic component. The harmonic cancellation module (HCM) is shown in Figure 7.

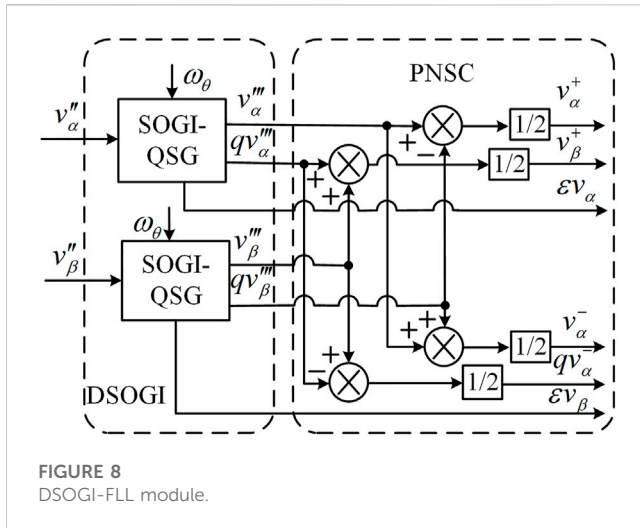


FIGURE 8
DSOGI-FLL module.

3.2.3 DSOGI-FLL module

The structure of DSOGI-FLL module is composed of SOGI-QSG, positive-/negative-sequence calculator (PNSC), SOGI-FLL, and SRF-PLL. The quadrature output characteristic of SOGI-QSG can be used to achieve orthogonal phase separation of the input grid voltage signals, and then the positive- and negative-sequence components of the grid voltage in the two-phase stationary coordinate system can be calculated by PNSC, as shown in Figure 8.

The SOGI-QSG resonant frequency ω_θ in the DSOGI is obtained from the frequency-locked loop (FLL), and SOGI-QSG + PNSC outputs the positive- and negative-sequence components with a stable frequency by using the phase-locked loop (PLL). The FLL and PLL structures are shown in Figure 9.

4 Simulation and verification

According to Figure 2, a three-phase LCL-type PCS simulation model using the MATLAB/Simulink was established. By analyzing the steady-state and dynamic performance of the three-phase LCL-type PCS system under the unbalanced power grid and harmonic power grid, the control performance of the proposed control strategy was verified.

The simulation parameters are set as follows: transformer-side inductor $L_1 = 2$ mH, grid-side inductor $L_1 = 1$ mH, filter capacitor $C_2 = 100$ μ F, DC-side voltage $u_{dc} = 650$ V, grid-side voltage $u_{sabc} = 220$ V, grid voltage frequency $f = 50$ Hz, and switching frequency $f_{sw} = 20$ KHz.

The setting of the LADRC controller parameters are as follows: LESO bandwidth $\omega_0 = 27,000$, controller bandwidth $\omega_c = 6,000$, LESO parameters $\beta_1 = 108,000$, $\beta_2 = 4.359 \times 10^9$, $\beta_3 = 7.1112 \times 10^{13}$, $\beta_4 = 5.3114 \times 10^{17}$, LSEF parameters $K_P = 2.16 \times 10^{11}$, $K_I = 9.3 \times 10^7$, and $K_2 = 18,000$.

4.1 Improved FLL performance verification

In order to verify the performance of the HCM-FLL proposed in this article, the Simulink platform is used to build a system simulation

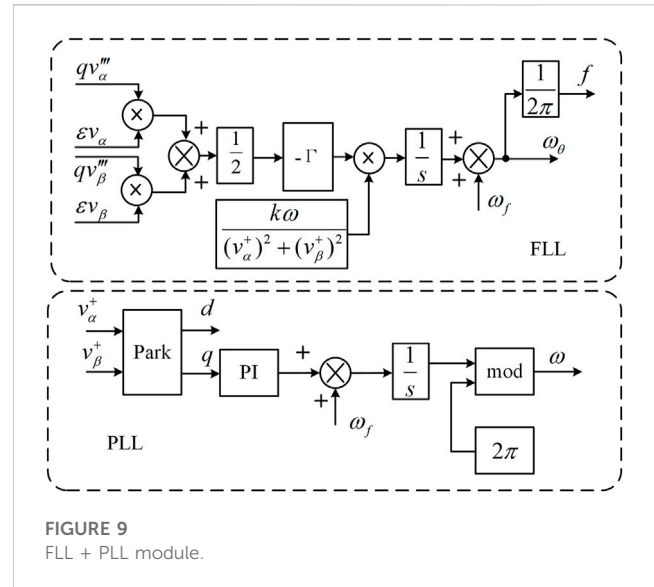


FIGURE 9
FLL + PLL module.

model, and the HCM-FLL and traditional DSOGI-PLL synchronization schemes are simulated and compared under the non-ideal grid, and the grid voltage frequency is set to 50 Hz.

In order to compare the phase-locking performance of HCM-FLL and traditional DSOGI-PLL under the unbalanced power grid, the grid voltage unbalance is set at 0.5 s, as shown in Figure 10A, and the phase-locking error of DSOGI-PLL and HCM-FLL is shown in Figure 10B. The comparison found that after introducing the unbalanced voltage after 0.5 s, the phase-locking errors of the two structures fluctuated to a certain extent and remained stable after several cycles. The phase-locking error of DSOGI-PLL was -0.3° , and the phase-locking error of HCM-FLL is close to 0. HCM-FLL can completely eliminate the influence of the unbalanced power grid and accurately track the phase information of the power grid under the unbalanced power grid.

In order to verify the performance of HCM-FLL and DSOGI-PLL under the harmonic grid, three-phase balance is maintained and 20% negative-sequence fifth harmonic and 14% positive-sequence seventh harmonic are injected into the grid at 0.5 s, as shown in Figures 10C; Figure 11D, which is a phase-locking error comparison between HCM-FLL and DSOGI-PLL under the harmonic grid. It can be seen from the figures that after adding harmonics in 0.5 s, DSOGI-PLL produces a relatively large phase-locking error, the fluctuation range is $+1.5^\circ \sim -3^\circ$, and the phase-locking error is still -0.2 after stabilization. By contrast, the fluctuation range of HCM-FLL is about $-1^\circ \sim +0.5^\circ$. After stabilization, the phase-locking error is close to 0. HCM-FLL can completely eliminate the influence of harmonics and accurately track the phase information of the grid under the harmonic grid.

4.2 Three-phase voltage unbalance in power grid

The voltage waveform of the three-phase unbalanced power grid is shown in Figure 11A. The LCL-type energy storage converter is set

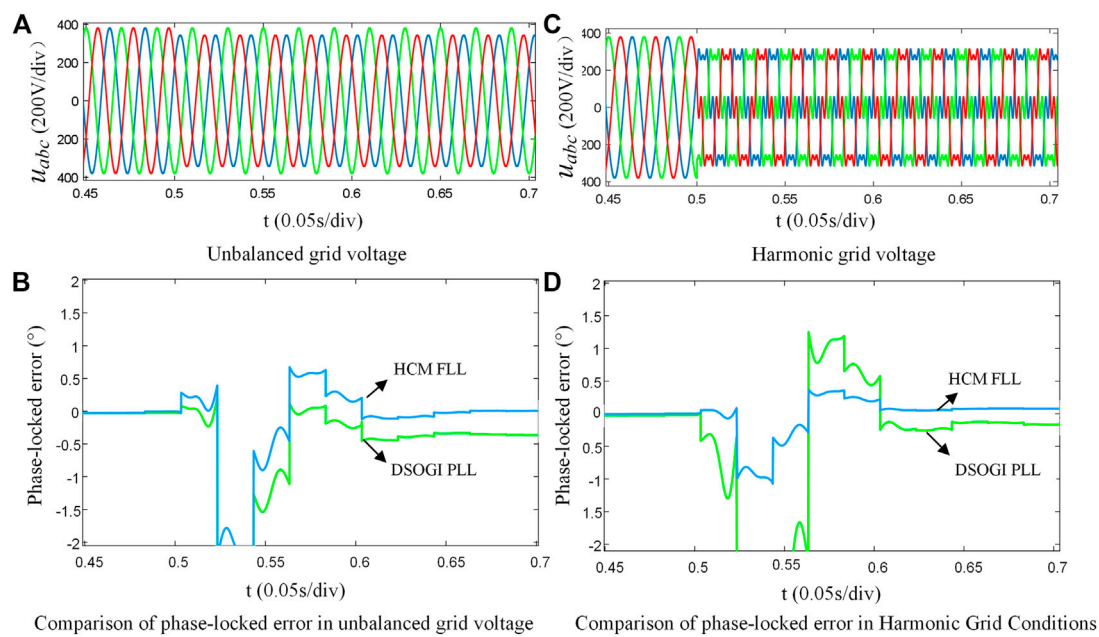


FIGURE 10

Phase-locked performance comparison.

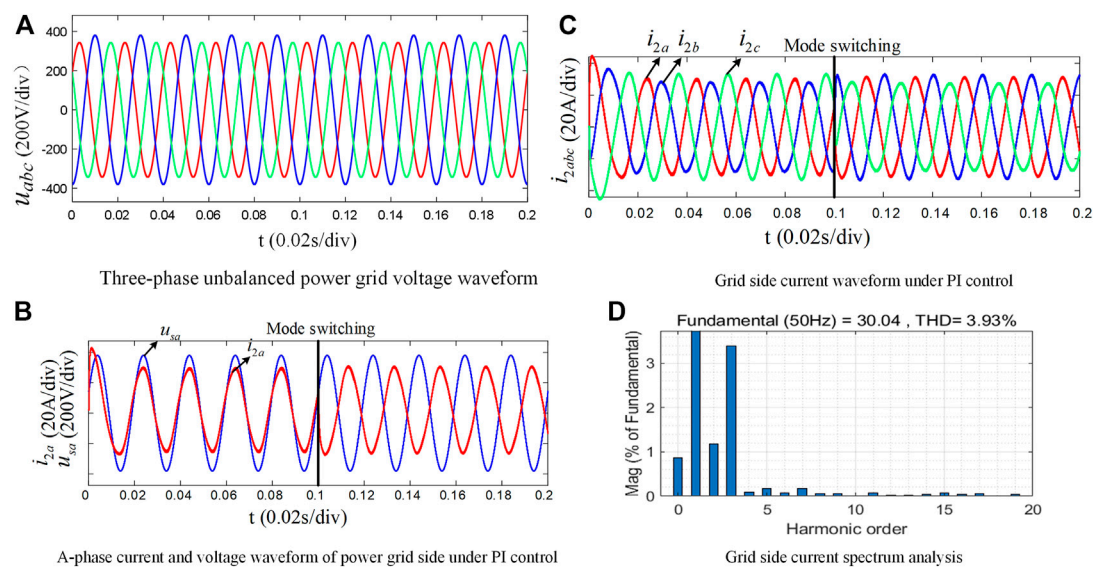


FIGURE 11

Simulation results of the traditional PI control strategy in three-phase unbalanced power grid.

to work in two states: before 0.1 s, the PCS works in the grid discharge mode with 30 A power, while after 0.1 s, the PCS works in the grid charge mode with 30 A power, and the Fourier analysis is conducted on the grid current under these two operating states, respectively.

Figure 11 shows the simulation results under the traditional PI control strategy. Figure 12 shows the simulation results under the

improved LADRC + HCM-FLL control strategy proposed in this article.

From Figure 11B, it can be seen that under the condition of three-phase grid unbalance, the traditional PI control strategy has the current and voltage in phase when the PCS operates in the inverter mode, with less current distortion. After 0.1 s, the PCS switches to the rectifier mode, and the current and voltage are 180° out of phase, with energy

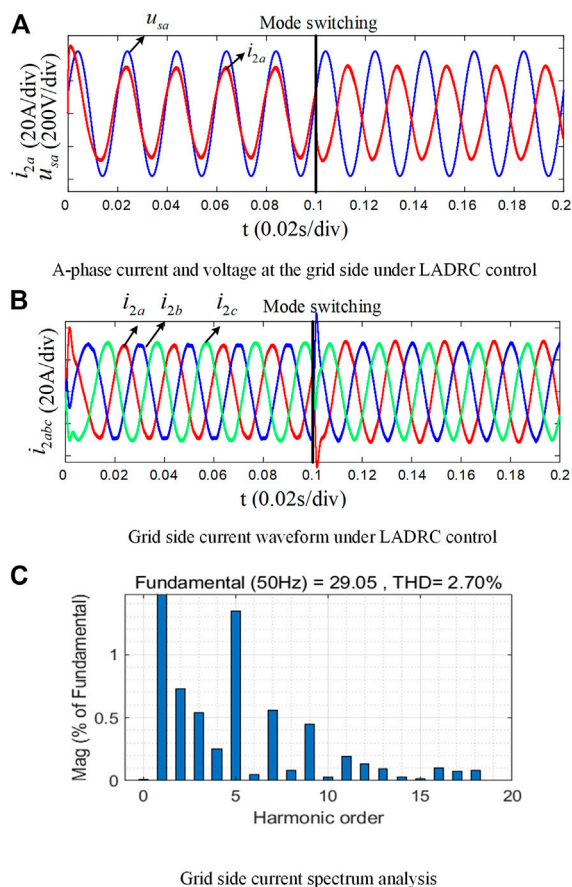


FIGURE 12
Simulation results of LADRC control in three-phase unbalanced power grid.

flowing from the grid side to the DC side. When compared with the inverter mode, the current waveform is significantly worse, and the third harmonic content of the grid-connected current is large, accounting for about 3.4%, and the Total harmonic distortion (THD) is 3.93%. This is because the same set of PI control parameters is used in both rectifier and inverter modes, and the PI controller is sensitive to changes in system parameters. After the system mode is switched, the control performance of the PI controller is reduced due to the changes in system parameters. From Figure 11C, it can be seen that under the condition of the three-phase grid voltage unbalance, the traditional PI control strategy outputs have unbalanced the three-phase grid-connected current with a large amplitude difference.

From Figure 12A, it can be seen that under the condition of three-phase grid voltage unbalance, the improved LADRC + HCM-FLL control strategy can maintain good current quality in both the rectifier and inverter modes, reflecting the good anti-parameter variation characteristics of the LADRC controller. Figure 12B shows that the three-phase grid-connected current output is balanced under the control of the improved strategy, and the amplitude difference is small. Figure 12C shows that when compared with the PI control strategy, the third- and fifth-harmonic content of the grid-connected current is significantly

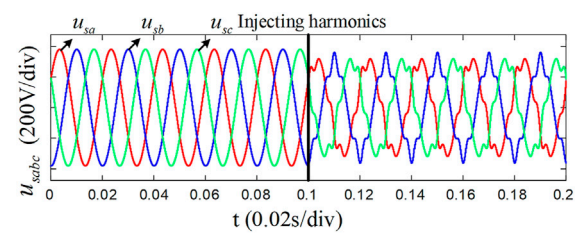


FIGURE 13
Voltage waveform of the three-phase harmonic power grid.

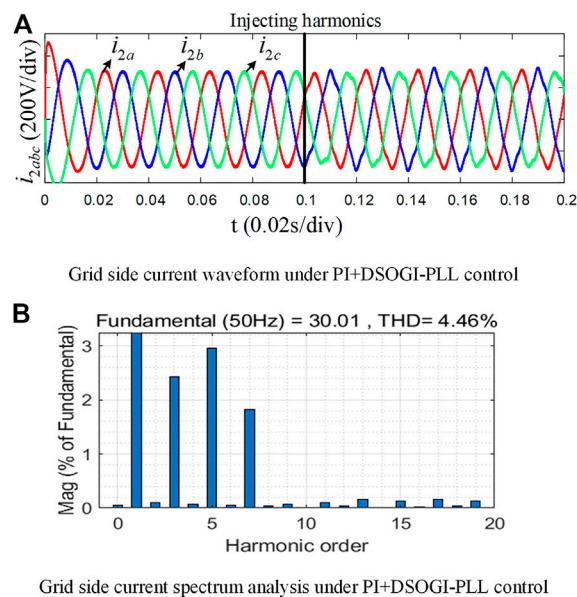


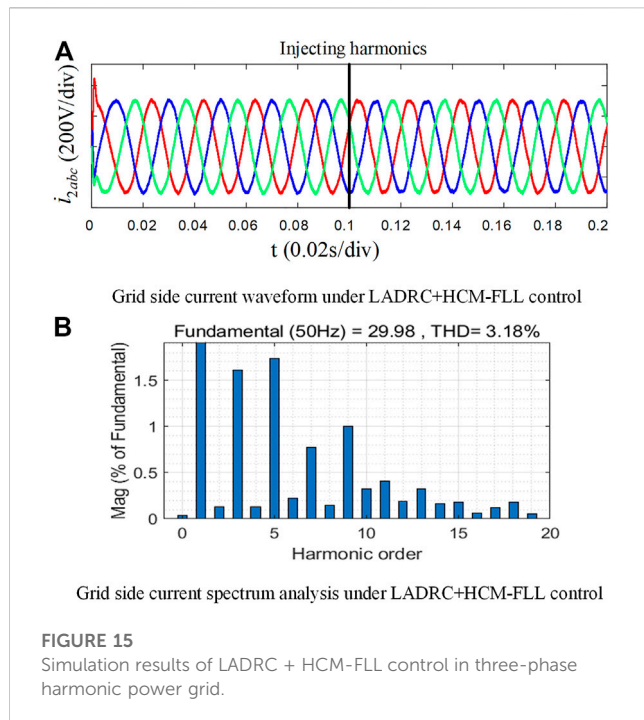
FIGURE 14
Simulation results of PI + DSOGI-PLL control in three-phase harmonic power grid.

reduced, accounting for about 0.6% when the total THD is 2.7%, which is a significant improvement over the PI control.

4.3 Harmonic grid condition

In order to study the anti-disturbance performance of the LADRC + HCM-FLL control strategy under harmonic power grid conditions, assuming that the power grid voltage is balanced and frequency is unchanged, the fifth and seventh harmonic components are injected at 0.1 s corresponding to 10% and 5% of the amplitude of the power grid voltage base wave, respectively, as shown in Figure 13.

It can be seen from Figures 14, 15 that both PI and LADRC current control based on HCM-FLL can better control the grid-side current under the harmonic grid. When compared with the PI control strategy, LADRC current control can better suppress the fifth and seventh harmonics of the grid-side current (about



1.3% and 1% reduction, respectively), resulting in a 1.28% reduction in the total THD and achieving better quality of the incoming grid current.

5 Conclusion

This article aims to address the issues of grid voltage unbalance and harmonic problems that the LCL-type PCS frequently encounters in microgrid environments. To achieve this, we analyzed the mathematical model of the LCL-type PCS, designed a linear active disturbance rejection controller based on model compensation, and investigated the influence of grid voltage unbalance and harmonics on the LCL-type PCS. Furthermore, we propose an active anti-disturbance control strategy for the LCL-type PCS based on a generalized second-order integrator frequency-locked loop. According to the simulation results presented in Section 3, our proposed control strategy offers the following benefits:

- (1) The HCM-FLL structure based on the specified number of harmonic elimination can effectively realize the conversion and independent control of the positive- and negative-sequence components of the power grid voltage and respond quickly and accurately to the working conditions such as power

grid voltage unbalance and harmonic grid conditions that have been generated in the microgrid environment.

- (2) In the traditional PI control strategy in the state of the unbalanced power grid voltage, the three-phase output of the grid-side current is unbalanced, with a large amplitude difference and high third-harmonic content. The LADRC current control strategy in this article can achieve good control of the grid-side current under the same conditions, with balanced three-phase current, small differences in amplitude, and the effective suppression of the third-harmonic content.
- (3) The traditional PI control strategy in the harmonic power grid has large current distortions on the grid side, unbalanced output current, and high harmonic content. The LADRC current control strategy in this article can effectively suppress the current harmonics on the grid side under the same conditions (when compared with PI, the fifth and seventh harmonics are reduced by about 1.3% and 1%, respectively), and the total THD is reduced by 1.28%. The current quality improvement effect is obvious.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

JY wrote the manuscript, SW provided the conceptual idea, and JY built the simulation environment.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process and Energy Systems Engineering, a section of the journal Frontiers in Energy Research

RECEIVED 31 December 2022

ACCEPTED 27 March 2023

PUBLISHED 05 April 2023

CITATION

Luo D, Chen W, Fang J, Liu J, Yang J and Zhang K (2023), GRU-AGCN model for the content prediction of gases in power transformer oil.
Front. Energy Res. 11:1135330.
doi: 10.3389/fenrg.2023.1135330

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GRU-AGCN model for the content prediction of gases in power transformer oil

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Aiming at high accuracy of dissolved gas content prediction in transformer oil, a novel method based on gated recurrent unit and adaptive graph convolution network (GRU-AGCN) is proposed. For gated recurrent unit (GRU) can selectively choose the feature of time series, it is used to extract time series information of the gas content. Correlation among gases are extracted to improve the accuracy. The original adjacency matrix of the model is constructed according to the grey relational analysis (GRA), and the dynamic relation information between gases is extracted by adaptive graph convolution network (AGCN). The experimental result shows that the GRU-AGCN model can efficiently extract the temporal features and perceive the dynamic relationship of gases. The predictions error of the proposed method is lower than that of RNN, LSTM network and GRU network. The proposed method provides a reliable and accurate result for the prediction of dissolved gas content in transformer oil.

KEYWORDS

power transformer, dissolved gas, time series prediction, gated recurrent unit, graph convolutional network

1 Introduction

Transformer is an important equipment in power system, which is related to the safety and stability of power system (Wu et al., 2021; Su et al., 2022). During the operation of the power transformer, several gases are generated in oil by the influence of life cycle, load, oil temperature and other factors. When the transformer overheats or discharges, there will be abnormal changes in gases (Gómez et al., 2014). Insulation will be broken down as the transformer fault develops, affecting the stability of the power system (Huang et al., 2021). Therefore, the state data of the power transformer can be obtained and its trend can be predicted by installing monitoring equipment on the transformer, which can provide a reliable judgment basis for the state maintenance of the transformer (Xie et al., 2020).

In recent years, a lot of research work has been done on the prediction of dissolved gas content in transformer oil. Chen et al. (2021) constructed an improved grey model for the time series prediction of gas in oil. K-nearest Neighbor was used to predict the furan level in transformers in (Shaban et al., 2016). In addition, many machine learning methods such as artificial neural networks (Ghunem et al., 2012) and support vector machines (Atherfold and van Zyl, 2020) are used for gas content prediction. The above methods process the data of each moment synchronously, so the feature significance of different moments cannot be considered, which means that their prediction accuracy is limited.

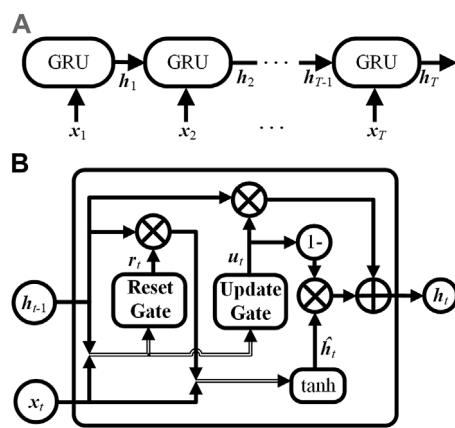


FIGURE 1
Structure of GRU network, (A) is GRU network overall structure,
(B) is GRU internal structure.

Recurrent neural network (RNN) extracts current and historical information by loop structure, which is suitable for processing time series. However, RNN is weak in learning information at too far time, which is called as “Long-term dependency problem.” The Long short-term Memory (LSTM) developed based on RNN introduces gating mechanism to alleviate the problem of RNN. Therefore, some prediction methods for gas content based on LSTM have been proposed (Lin et al., 2018b; Ma et al., 2021). But the complexity of LSTM leads to long training time. Gated Recurrent Unit (GRU) network was proposed as another variant of RNN, simplifies the gating mechanism, which can process long series efficiently and be trained fast (Minh et al., 2018).

There are complex dynamic relationships in gases in transformer oil (Fessler et al., 1989). When the hot spot temperature is low or the fault is slight, the insulating material produces hydrogen and alkanes through decomposition. When the fault is severe, the energy will be released by overheating or discharge, alkenes and alkynes will be produced by further decomposition. Therefore, the production of dissolved gases in oil has a certain correlation, and varies according to the fault type and development. Above methods are based on the prediction by single gas variable, which ignores the inherent correlations between gases, and the results are obtained with low accuracy and reliability. In the study of (Ma et al., 2021), temperature and seven gas content series were put into LSTM to predict gas content. Lin et al. (2018a) took the gas content and the ratios of various gas as the input features of neural network for the prediction. These methods consider the influence of various factors in the prediction, but the feature extraction methods of correlation factors are simple, and the promotion in prediction performance is limited.

For above problems, a content prediction method of gas in transformer oil based on gated recurrent unit and adaptive graph convolution network (GRU-AGCN) is proposed. GRU is used to extract time series information of gas content. To describe the correlation among gases, the original adjacency matrix of the model is constructed based on grey correlation analysis (GRA), and the adjacency matrix is real-time updated according to the input

to ensure that the correlation obtained is accurate and reliable. The dynamic relation feature among gases is extracted by adaptive graph convolution network (AGCN). The accurate prediction of gas content can be achieved by integrating the historical information of gas itself and other relevant gas information.

2 Gated recurrent unit network

GRU network is one of the variants of RNN. In GRU, gating mechanism is introduced to RNN to selectively transmit temporal features.

The structure of GRU network is shown in Figure 1A. Data $[x_1, x_2, \dots, x_T]$ with length T are input into corresponding units chronologically. The structure of GRU is shown in Figure 1B. Take GRU of time t as an example ($1 < t < T$), the input of the unit includes current original data x_t and hidden feature h_{t-1} output by the last unit. And the output of the unit is the hidden feature at time t denoted as h_t . The workflow of GRU is as follows, Firstly, input is passed to reset gate and update gate to obtain reset state r_t and update state u_t . Secondly, the candidate hidden state $\hat{h}_t$ at time t is calculated by reset state r_t . Finally, the hidden feature h_t at time t is updated by combining the updated state u_t with the hidden feature h_{t-1} at time $(t-1)$ and candidate hidden state $\hat{h}_t$ at time t . The working principle is written as follows:

$$r_t = f_{\text{sig}}(x_t w_{r1} + h_{t-1} w_{r2} + B_r) \quad (1)$$

$$u_t = f_{\text{sig}}(x_t w_{u1} + h_{t-1} w_{u2} + B_u) \quad (2)$$

$$\hat{h}_t = f_{\text{tanh}}(x_t w_{h1} + r_t \otimes h_{t-1} w_{h2} + B_h) \quad (3)$$

$$h_t = u_t \otimes h_{t-1} + (1 - u_t) \otimes \hat{h}_t \quad (4)$$

In above equations, $f_{\text{sig}}(\cdot)$ and $f_{\text{tanh}}(\cdot)$ are sigmoid function and hyperbolic tangent function, W_{r1} and W_{r2} are the weight of the reset gate, B_r is the bias of the reset gate, W_{u1} and W_{u2} are the weight of the update gate and B_u is the bias of the update gate. W_{h1} and W_{h2} are the weight and B_h is the bias in the candidate hidden state calculation. Hadamard Product operation is denoted as.

By above principle, historical information and current information can be filtered and processed flexibly in GRU network.

3 Adaptive graph convolutional network

3.1 Grey relational analysis of gases in transformer oil

GRA is an analysis method based on grey system theory, which judges the correlation degree among factors according to the similarity of the shape of the factor curves. Therefore, the historical data of gas 1~ n with length M are analyzed by GRA.

Historical data for gas i is used as a reference sequence, which is denoted as $X_M^i = [x_1^i, x_2^i, \dots, x_M^i]$, and take the historical data of gas j as a comparison sequence, which is denoted as $X_M^j = [x_1^j, x_2^j, \dots, x_M^j]$, where $i, j \in \{1, 2, \dots, n\}$, and $i \neq j$. Grey correlation coefficient $coeff_{ij}$ and grey relational degree $grey_{ij}$ are calculated as follows,

$$\begin{cases} \text{coeff}_{ij}(m) = \frac{\min|X_M^i - X_M^j| + \alpha \cdot \max|X_M^i - X_M^j|}{|x_m^i - x_m^j| + \alpha \cdot \max|X_M^i - X_M^j|} \\ \text{grey}_{ij} = \frac{1}{M} \sum_{m=1}^M \text{coeff}_{ij}(m) \end{cases} \quad (5)$$

$\text{coeff}_{ij}(t)$ is the correlation coefficient of reference sequence and comparison sequence at time t , the minimum and maximum values of the absolute difference between the reference sequence and other comparison sequences are denoted as $\min|X_M^i - X_M^j|$; $\max|X_M^i - X_M^j|$, $\alpha \in (0, 1)$ is resolution factor, which determines the distribution of grey_{ij} . To avoid the distribution of GRA being too compact or too sparse, it is appropriate to set α at 0.5.

If the grey relational degree $\text{grey}_{ij} \in (0, 1)$ obtained is close to 1, it indicates that gas j and gas i have a strong correlation. Otherwise, the correlation between gas j and gas i is weak. GRA preliminarily determined the correlation information among gases in oil.

3.2 Graph convolutional network

Graph convolutional network is designed to realize information fusion and feature extraction of graph data with complex association by means of adjacency matrix and graph kernel. Therefore, in this paper, the gas in oil is taken as the graph node, the result of GRA constitute edges, and the weighted gas adjacency matrix A_0 is constructed based on the grey relational degree to extract the gas correlation features.

Traditional adjacency matrix can only describe the connection between nodes, that is, if there is an edge between node i and node j , the element a_{ij} in adjacency matrix is 1, otherwise, it is 0, which cannot express the strength of connections. Based on the results of GRA in the last section, the element a_{ij} of gas adjacency matrix is redefined as follows,

$$a_{ij} = \begin{cases} \text{grey}_{ij}, i \neq j \\ 0, i = j \end{cases} \quad (6)$$

The gas original adjacency matrix A_0 (dimension $n \times n$) is obtained by above equation.

To make the gas node introduce its own features in the graph convolution operation, self-loop is added to the gas node in the graph, and the graph convolution network is as follows,

$$f_{GCN}(\mathbf{H}) = f_{\text{sig}}(\mathbf{D}^{-1/2}(\mathbf{I} + \mathbf{A}_0)\mathbf{D}^{-1/2}\mathbf{H}\mathbf{W}_G + \mathbf{B}_G) \quad (7)$$

Where $\mathbf{H}$ (dimension $n \times C_{\text{hidden}}$) is the input feature of gas node 1~ n , denoted as $\mathbf{H} = [\mathbf{h}^1, \mathbf{h}^2, \dots, \mathbf{h}^n]$, $\mathbf{W}_G$ (dimension $C_{\text{hidden}} \times C_{\text{out}}$) is the graph convolution kernel, $\mathbf{B}_G$ (dimension $n \times C_{\text{out}}$) is the graph convolution bias, and $\mathbf{D}$ (dimension $n \times n$) is degree matrix, which is the diagonal matrix composed of the number of edges of gas node 1~ n in the graph with self-loop. The self-loop refers to the edge where node links to itself, which avoid the omission of node itself caused by only extracting neighbor node information in feature update. In gas prediction, the self-loop enables the model to consider the original features of the gas when extracting related gas features.

3.3 Reconstruction of adjacency matrix and adaptive graph convolution networks

To capture real-time dynamic gas state information, the original graph convolution algorithm is improved. In the improved model, the original static adjacency matrix A_0 is modified to a variable that changes adaptively according to the input feature $\mathbf{H}$. A learnable distance measure is introduced into the adjacency matrix. The distance dist_{ij} between input feature $\mathbf{h}^i$ (dimension $1 \times C_{\text{hidden}}$) of gas node i and input feature $\mathbf{h}^j$ (dimension $1 \times C_{\text{hidden}}$) of gas node j is proposed as follows,

$$\text{dist}_{ij} = \sqrt{(\mathbf{h}^i \mathbf{W}_d)(\mathbf{h}^j \mathbf{W}_d)^T} \quad (8)$$

Where $\mathbf{W}_d$ (dimension $C_{\text{hidden}} \times C_{\text{hidden}}$) is a learnable weight matrix.

Gaussian function could improve data differentiation, map distance dist_{ij} non-linear to $[0,1]$, and enhance the expression ability of gas correlation. Here, Gaussian function is used to process distance measurement, and reconstructed adjacency matrix elements are obtained. Specific formula is as follows,

$$f_{\text{Gauss}}(\text{dist}_{ij}) = \exp\left(-\frac{\text{dist}_{ij}^2}{2\sigma^2}\right) \quad (9)$$

In the formula, $\exp(\cdot)$ is an exponential function based on the constant e , σ is a bandwidth, which adjusts the influence range of the Gaussian.

The reconstructed adjacency matrix A_{rec} (dimension $n \times n$) is obtained by above steps, which is expressed as:

$$\mathbf{A}_{\text{rec}} = f_{\text{Gauss}}\left(\sqrt{\mathbf{H}\mathbf{W}_d\mathbf{W}_d^T\mathbf{H}^T}\right) \quad (10)$$

The reconstructed adjacency matrix A_{rec} is introduced into the graph convolution formula, which is used as a modification to the original adjacency matrix A_0 , and adaptive graph convolution network formula is shown as follows:

$$f_{\text{AGCN}}(\mathbf{H}) = f_{\text{sig}}(\mathbf{D}^{-1/2}\mathbf{A}_{\text{adapt}}\mathbf{D}^{-1/2}\mathbf{H}\mathbf{W}_G + \mathbf{B}_G) \quad (11)$$

Where $\mathbf{A}_{\text{adapt}} = \mathbf{I} + \mathbf{A}_0 + \mathbf{A}_{\text{rec}}$. It means that the model can learn the current optimal gas relationship from the gas relationship information obtained by GRA. For the learning range is small, the model converges quickly through the training.

4 Realization of GRU-AGCN model for gas content prediction

4.1 GRU-AGCN model design

Traditional methods focus on the single gas sequence but concerns little on the correlation information among gases, and their ability to perceive transformer operation status is limited. In addition, some prediction models with multiple gases also lack effective ways to analyze and extract correlation information of input features. The above problems lead to low stability and reliability of gas content prediction in transformer oil.

Therefore, a GRU-AGCN model for gas content prediction is designed in this paper. The model structure is shown in Figure 2. The model takes the content series of T time points of gas 1~ n as input, the temporal features of each gas are extracted through several parallel GRU networks. And temporal features of gases from GRU networks are input into AGCN to extract the gas dynamic correlation features. AGCN firstly calculates the distance measure between gases according to the time series features, and updates the adaptive adjacency matrix based on the original adjacency matrix obtained by GRA. Then, the updated graph adjacency matrix and temporal features are passed into the graph convolution for feature fusion and feature transformation. Finally, the predicted values of gas contents at time $(T + 1)$ are output by linear layer and activation function.

4.2 Prediction process based on GRU-AGCN model

Content prediction process of gases in transformer oil based on GRU-AGCN model are as follows,

- 1) Obtain historical data of gas content in transformer oil.
- 2) Remove the outliers in the gas content data and fill in the gaps by interpolation.
- 3) Normalize the content data of each gas.
- 4) The normalized data are rolled and intercepted into multiple groups of samples based on the time length T , and sample set is separated into training set and test set.
- 5) Based on the training set, the relational degrees of gases are obtained by GRA, and original gas topology and adjacency matrix A_0 are constructed.
- 6) The smoothed mean absolute error is set to be loss function. And Adam optimization algorithm is used to make the model learn training samples. After several iterations of training and parameters adjusting, the prediction requirement could be satisfied by the model.
- 7) The test set samples are input to model obtained in Step (6) for prediction test, and the predicted results are analyzed.

5 Analysis of experimental examples

To verify the superiority of the proposed model, a GRU-AGCN model is built by Python language based on Spyder platform and PyTorch library.

Mean absolute error (MAE) and mean absolute percentage error (MAPE) are used to evaluate the prediction performance of the model. Suppose that gas content series in time 1~ t is used for prediction, denoted as $\mathbf{X} = [x_1, x_2, \dots, x_t]$, the corresponding predicted value series is denoted as $\mathbf{Y} = [y_1, y_2, \dots, y_t]$. The MAE and MAPE are calculated as follows:

$$f_{\text{MAE}}(\mathbf{X}, \mathbf{Y}) = \frac{1}{t} \sum_{i=1}^t |x_i - y_i| \quad (12)$$

$$f_{\text{MAPE}}(\mathbf{X}, \mathbf{Y}) = \frac{1}{t} \sum_{i=1}^t \frac{|x_i - y_i|}{y_i} \quad (13)$$

A converter transformer in Henan Province is taken as the research object. It was put into operation in 2014 and has been

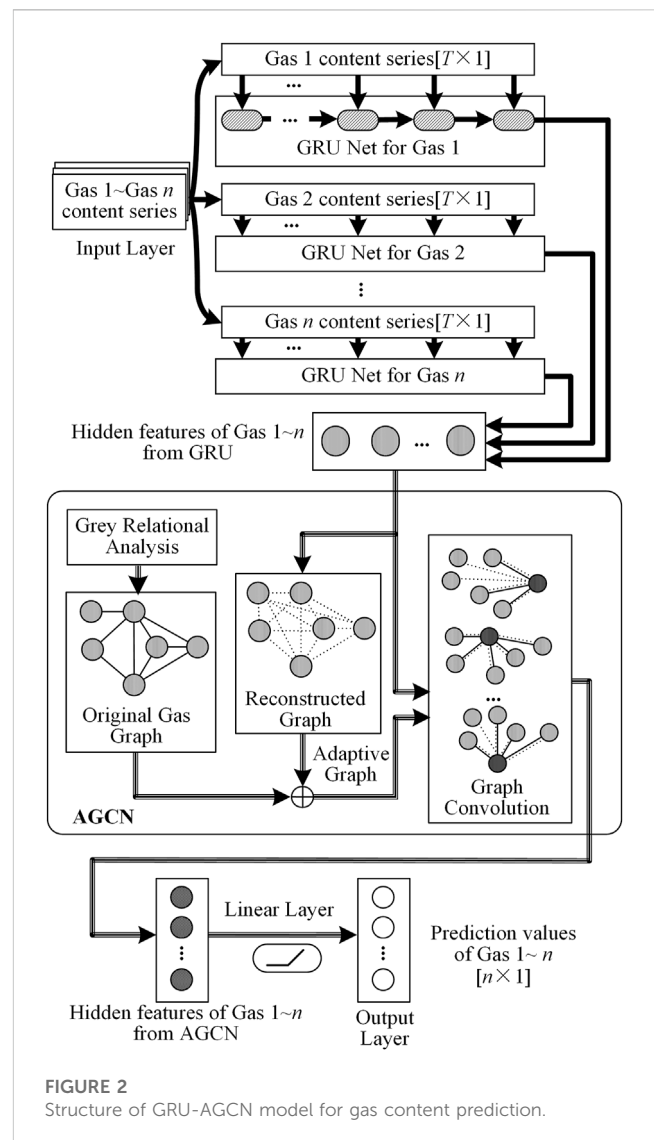


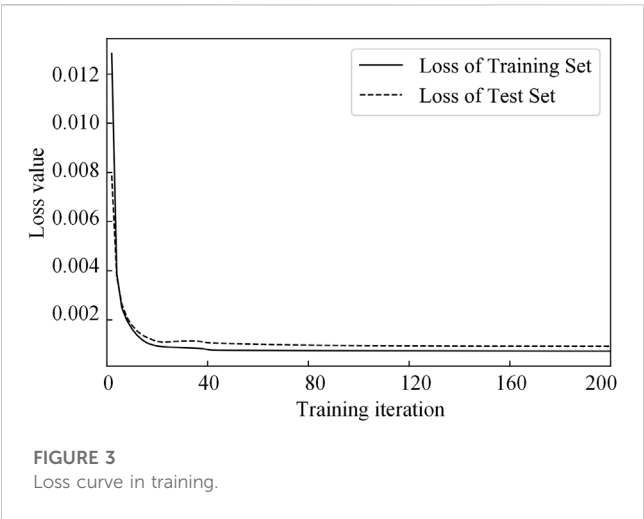
FIGURE 2
Structure of GRU-AGCN model for gas content prediction.

operating normally ever since. Dissolved gases monitored include hydrogen (H_2), methane (CH_4), ethane (C_2H_6), ethylene (C_2H_4), acetylene (C_2H_2), carbon monoxide (CO) and carbon dioxide (CO_2), and their content is within the normal range stipulated by IEC. Eight hundred and twenty sets of data of the transformer from May to October 2019 were selected for the experiment. The time period is 4 h. The content of C_2H_2 is always 0 in the monitoring interval, which is not used as model input. The input of the model is set as the content series of six gases in 20 consecutive time points, and the output is set as the predicted value of gases at the next time point. The original gas content data are processed according to the above steps and 800 groups of samples were obtained. The size of training set and test set are divided by 3:1. The first 600 groups are set as the training set, and the last 200 groups are the test set.

The grey relational degree table of six gas content is obtained by GRA. As shown in Table 1, the correlations rang is distributed in [0.634, 1.000], which indicates that there are clearly exists correlations among six gases, but their intensity are different. Regardless of the self-correlation, CO and CO_2 are the most correlated, while the correlation between H_2 and CO_2 is the weakest.

TABLE 1 Grey relational degree of gases in transformer oil ($\alpha = 0.5$).

References	Comparison					
	H ₂	CH ₄	C ₂ H ₆	C ₂ H ₄	CO	CO ₂
H ₂	1.000	0.675	0.713	0.694	0.646	0.634
CH ₄	0.675	1.000	0.763	0.727	0.815	0.807
C ₂ H ₆	0.713	0.763	1.000	0.767	0.749	0.733
C ₂ H ₄	0.694	0.727	0.767	1.000	0.665	0.661
CO	0.646	0.815	0.749	0.665	1.000	0.854
CO ₂	0.634	0.807	0.733	0.661	0.854	1.000



Based on Table 1, the correlation degrees are introduced into AGCN of the model as original adjacency matrix. And parameter σ^2 in the AGCN is set to 0.5, because it achieves the best result in model training.

Then, GRU-AGCN model is trained for 200 times, and the initial learning rate is set to 0.0005. The sample loss curve in Figure 3 is obtained. As shown in Figure 3, the model parameters converge to the global optimum quickly and smoothly during training.

To verify the accuracy and reliability of the proposed model in gas content prediction task, the GRU-AGCN model and other

TABLE 3 Effects of models on CO₂ content prediction.

Model type	MAE (%)	MAPE (%)	Training time (s)
GRU-AGCN	1.95	3.18	289.9
GRU-GCN	3.17	4.50	275.8
LSTM-GCN	3.32	4.59	1188.8
GRU Net	3.31	4.67	269.3
LSTM Net	3.56	4.99	1149.6
RNN	4.43	6.04	221.3

traditional models are used for single-step prediction experiment. The models used for comparison include RNN and its variants GRU Net and LSTM Net. In addition, original GCN is introduced into GRU Net and LSTM Net to form new models, denoted as GRU-GCN and LSTM-GCN respectively. Specific parameter settings of models are shown in Table 2.

Except for the model proposed in this paper and models introduced GCN, all other models are designed for univariate prediction. The input time scale, prediction range and training conditions of all models remained consistent. Hidden features of models are output through a linear layer and ReLU activation function. All models were trained 200 times.

Limited by space, this section mainly analyzes the result of CO₂ content prediction experiment. Table 3 records the training time and prediction effect of CO₂ content prediction by above models.

Firstly, RNN and its variants GRU Net and LSTM Net are compared. Obviously, RNN has the fastest training, but its prediction accuracy is far lower than other networks. Both GRU Net and LSTM Net introduce gating mechanism, which selectively extract features at different moments. Compared with RNN, MAE percentage of the two models decreased by 1.12 and 0.87 respectively. However, the training time of LSTM Net is much longer than that of GRU Net. It is proved that GRU Net can extract temporal features of gas content efficiently and is easier to train than LSTM Net.

Then, GRU Net and LSTM Net are compared with GRU-GCN and LSTM-GCN respectively. The prediction accuracy of model introduced GCN is significantly higher than the original model. The reason lies in that the information of the related gases has been used for the prediction by GRU in GRU-GCN model and LSTM-GCN model.

TABLE 2 Parameters of prediction models.

Model type	Input dimension	Output dimension	Number of layers	Hidden dimension
GRU-AGCN	6 × 20	6 × 1	GRU:1 AGCN:1	[20, 10]
GRU-GCN	6 × 20	6 × 1	GRU:1 GCN:1	[20, 10]
LSTM-GCN	6 × 20	6 × 1	GRU:1 GCN:1	[20, 10]
GRU Net	20	1	1	20
LSTM Net	20	1	1	20
RNN	20	1	2	[20, 10]

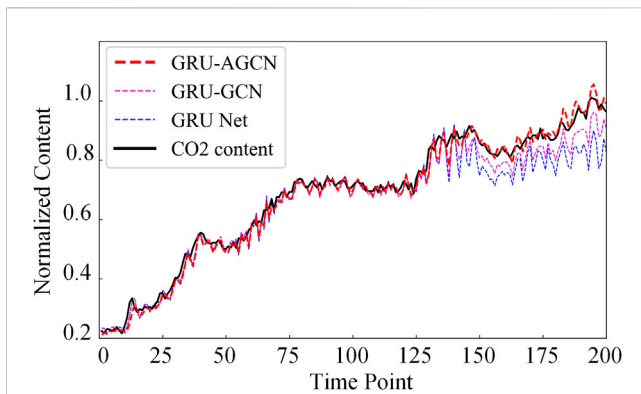


FIGURE 4

The effect of three models on CO₂ content prediction.

Finally, GRU-AGCN model is compared with GRU Net and GRU-GCN model. The prediction result by above models are shown in Figure 4. Based on the analysis of Figure 4 and Table 3, it can be found that GRU Net model only accurately predict the stable development of CO₂, as shown in 1st~125th point of Figure 4, which shows a poor prediction effect on series with large fluctuation. The GRU-GCN utilized the correlations between the gases. But the model cannot obtain satisfactory prediction effect in long time span, because the real-time changes in gas relationships cannot be represented by static adjacency matrices. The proposed GRU-AGCN model has the smallest MAE and MAPE in prediction, which is only 20.6 s slower than GRU Net during the training. The proposed method obtains the best effect with an acceptable time cost. The reason is that GRU part of the proposed model can efficiently extract the temporal features of gas series, while the AGCN part adaptively adjust the graph adjacency matrix and dynamically acquire the gas relationship from learning samples, which makes the prediction result more accurate and reasonable than other models. The proposed model keeps high accuracy and reliability for series in stable situation or large fluctuations.

6 Conclusion

The change of gas content in transformer oil reflects the health status of transformer, which needs to consider both the temporal information from gas itself and the dynamic correlation information from related gases. Base on above two aspects, a prediction method based on GRU-AGCN model is proposed. From the experiment comparison and analysis, it can be concluded that:

- 1) GRU Net can extract key information of important moments from gas series, and its prediction is more accurate than RNN. Compared with LSTM Net, GRU Net is simpler, training faster, and extraction efficiency for the temporal features is higher.

- 2) Compared with the single gas variable prediction model, the multi-gas variable combined prediction model with GCN consider the correlation between gases, which significantly improves the prediction accuracy.
- 3) The AGCN proposed in this paper extracts the gas relations dynamically, which makes the prediction result more accurate and reasonable. The proposed model can maintain high accuracy for different time period.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

DL and WC contributed to the development and design of the model. JF implemented the programming of the proposed model algorithm. JL collected experimental data. JY and KZ designed the experiment to prove the superiority of the proposed method. All authors wrote parts of the manuscript. All authors have read and agreed to the submission of the manuscript.

Funding

The research is supported by the Science and Technology Project of State Grid Shanxi Electric Power Co., LTD., China (No. SGSXJC00YCJS2100679).

Conflict of interest

Authors WC, JL, JY, and KZ were employed by State Grid Jincheng Power Supply Company.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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OPEN ACCESS

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SPECIALTY SECTION

This article was submitted to Process
and Energy Systems Engineering,
a section of the journal
Frontiers in Energy Research

RECEIVED 09 February 2023

ACCEPTED 30 March 2023

PUBLISHED 18 April 2023

CITATION

Sheng K, Xie C, Sha J, Zeng Z, Liu Y, Lei C,
Chen L and Wu Y (2023), Opinions on
power grid infrastructure planning with
investment risks.
Front. Energy Res. 11:1162068.
doi: 10.3389/fenrg.2023.1162068

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Opinions on power grid infrastructure planning with investment risks

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KEYWORDS

deep learning, duration prediction, feature extraction, investment risk, power grid planning

1 Introduction

Power grid infrastructure planning schemes are usually affected by various investment risks in the construction duration, such as financial risks (Ammar and Eling, 2015; Zhao et al., 2022), power demand changes (Li et al., 2022; Yang et al., 2022), and extreme climates (Cao et al., 2022). Due to these investment risks, the actual completion date of power grid infrastructure projects may be delayed, and thus the electricity demand for load growth and renewable energy integration cannot be well satisfied (Dang et al., 2019). A few investigations have been reported in the literatures (Pan et al., 2022; Wu et al., 2022) to accurately predict the infrastructure project durations. For example, various prediction models with neural networks and multiple linear regression methods based on historical infrastructure planning data were presented for project duration forecasting (Pan et al., 2022). However, the investment risks affecting the planned infrastructure projects are neglected, and these risks are important factors for the construction duration prediction problem. Therefore, this paper aims to offer insightful opinions and discussions on the power grid infrastructure planning and project duration prediction problems with investment risks.

The main contributions of this paper are twofold as listed: 1) a multi-factor risk evaluation model was formulated based on program evaluation and review technique (PERT) for power grid infrastructure planning under financial risk, extreme climates, and electricity demand changes. Various curve features are extracted from historical infrastructure project schedules using Tsfresh tool, and vital risk features are identified based on a feature filtering method; 2) a project duration prediction method is proposed based on Bayesian neural network (BNN) considering multi-factor investment risks to formulate the occurrence probability of infrastructure project delay, and hence the deferred duration of different infrastructure projects can be quantified for smart grid planning.

2 Risk factors affecting power grid infrastructure planning

In the implementation process of power grid infrastructure planning, there are various internal and external risk factors such as financial risks, electricity demand variations, and extreme weather events (Ammar and Eling, 2015). First, power grid infrastructure planning is greatly affected by financial risks, such as the movement of interest rates, exchange rates, and cash flows. Second, due to the grid integration of massive electric vehicles with charging

behavior uncertainties, electricity demand variations are inevitable (Castillo et al., 2022). Third, there are various weather risks such as hurricanes, cold snaps, rainstorms, heat waves, and thunderstorms battered power grid infrastructure planning (Cao et al., 2022). The occurrence of significant infrastructure project delay may lead to severe financial losses even if the infrastructure project itself does not sustain physical damage. As a result, based on the PERT, to quantify investment risk factors, the impact of each risk factor can be determined through Monte Carlo simulation (Quah and Quek, 2007; Cheng et al., 2021). In summary, the triangular distribution can be given for a multi-factor risk evaluation model to formulate the occurrence probability of financial risks, electricity demand variations, and extreme climates in this paper.

3 Feature extraction of infrastructure project schedules

Infrastructure project schedules can be characterized by investment and construction completion rate curves. Hence, Tsfresh and feature filtering methods are used to identify vital sequential features affecting power grid infrastructure planning from investment and construction completion rate curves (Ehya et al., 2022). Based on hypothesis testing, the feature filtering method is applied to evaluate the correlation between the project duration T and the sequential feature x extracted using the Tsfresh method. First, at the significance level α of 0.05, the null hypothesis indicates that the sequential feature x is not relevant to the project duration T and should not be retained. Second, each sequential feature x is scored by formula (1). The closer scores are to 1, the higher the occurrence probability of infrastructure project delay will be (Chen et al., 2022). Finally, the threshold Q_α can be obtained based on the significance level and the number of infrastructure projects. If $Q \geq Q_\alpha$, the null hypothesis is rejected, and the sequential feature x is retained. Otherwise, the null hypothesis is accepted, and the sequential feature x is removed. The correlation degree between project duration T and sequential feature x is calculated as follows:

$$Q(x, T) = \begin{cases} \max|F_{1,n}(T) - F_{0,n}(x)|, & \text{if } x \text{ is a Boolean type variable} \\ \frac{2[N_1(x, T) - N_2(x, T)]}{n(n-1)}, & \text{if } x \text{ is a continuous-valued type variable,} \end{cases} \quad (1)$$

where $F_{0,n}(x)$ and $F_{1,n}(T)$ are two cumulative distributions of the extracted curve feature and infrastructure project duration; n is the number of extracted curve features; $N_1(x, T)$ and $N_2(x, T)$ are the number of positively correlated element pairs and the number of negatively correlated element pairs, respectively.

Hence, more than 200 vital sequential features consisting of dynamic time-warping (DTW) distance, linear least-squares regression, time lagged cross correlation (TLCC), Spearman correlation coefficient, and enclosed area between investment and construction completion rate curves can be identified based on the feature filtering method for the project duration prediction method. Furthermore, in order to investigate the coordination degree of investment and construction completion schedules, the curve coordination degree of sequential features is proposed as follows:

$$K = \lambda_1 \cdot x_{DTW} + \lambda_2 \cdot x_{TLCC} + \lambda_3 \cdot x_\rho + \lambda_4 \cdot x_{AR}, \quad (2)$$

where x_{DTW} denotes DTW distance between investment and construction completion rate curves; x_{TLCC} represents the degree of the construction completion rate curve lagging behind the investment completion rate curves; x_ρ denotes the Spearman correlation coefficient; x_{AR} denotes the enclosed area between investment and construction completion rate curves; and λ_1 – λ_4 denote corresponding weights which can be obtained by the coefficient of the variation method. In this article, their values are 27.4%, 25.9%, 18.7%, and 28.1%, respectively.

Meanwhile, it can be found that infrastructure projects with critical features, including higher voltage levels, larger planning capacities, location in backcountry areas, and hysteretic investment, tend to result in higher delay risks.

4 Deep learning-driven project duration prediction with investment risks

Due to various investment risk factors affecting the power grid infrastructure planning, the project duration prediction problem can be transformed into a probabilistic forecasting model. Consequently, a deep learning-driven Bayesian method (Jia et al., 2021) is proposed to formulate the occurrence probability distribution of infrastructure project delay and quantify the deferred duration of different projects under diverse investment risks. The BNN algorithm can learn from the historical data of project duration and respond to changes in future variables with credibility. With conducting deep learning model training, the internal relationship between risk factors and infrastructure duration from historical data can be found efficiently.

The BNN structure is made up of input layer, hidden layer, and output layer. The hidden layer is a probability layer, while the weight ω in the probability layer obeys Gaussian distribution with mean μ and variance δ (Thiagarajan et al., 2022). The BNN-driven power grid infrastructure project duration prediction process with investment risks can be divided into the following steps:

- implementing the tri-layer BNN structure to formulate a deep learning-driven project duration prediction model with identified sequential features and investment risk factors as input data.
- training the BNN prediction model for exploring the non-linear relationship between sequential feature input data and project duration to determine the posterior distribution of weights.
- using historical project delay data of power grid infrastructure planning to verify the validity of the proposed model and obtain the duration delay probability distribution results.

With the proposed project duration prediction model, the power grid infrastructure projects data $D = (X, T)$ are given to train the project duration prediction model. X is the input data consisting of project labels, investment risk factors, curve coordination degree, and sequential features extracted from investment and construction

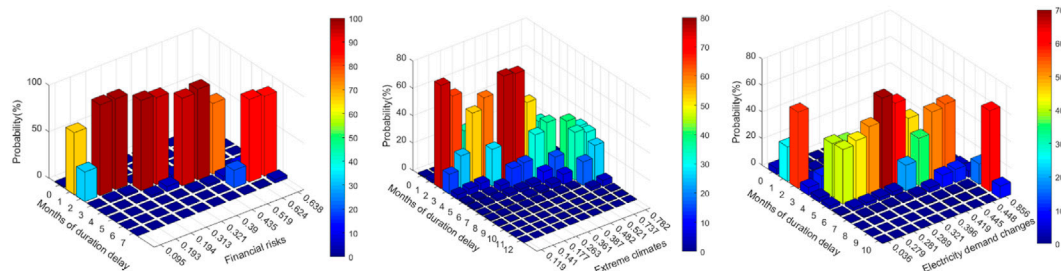


FIGURE 1

Occurrence probability distributions of infrastructure project delay under different risk factors.

completion rate curves. Project labels include project location, planning capacity, and theoretical duration. While T denotes the duration of power grid infrastructure projects. The triangular distribution parameters of financial risks, extreme climates and electricity demand variations are (0, 0.3, 1), (0, 0.2, 1), and (0, 0.4, 1), respectively.

Variational inference is introduced into network training to obtain the posterior distribution $P(\omega|D)$ of BNN weights suitable for duration prediction under different investment risks (Zhang et al., 2019). An existing simple distribution $q(\omega|\theta)$ is introduced to approximate the weight posterior distribution $P(\omega|D)$ by minimizing the difference between the two distributions. The weight distribution can be optimized by minimizing KL divergence, as follows:

$$\begin{aligned}\mathcal{L} &= \arg \min_{\theta} KL[q(\omega|\theta)||P(\omega|D)] \\ &= \arg \min_{\theta} \mathbb{E}_{q(\omega|\theta)} \left[\log \left[\frac{q(\omega|\theta)}{P(D|\omega)P(\omega)} \right] \right],\end{aligned}\quad (3)$$

where $\theta = (\mu, \sigma)$ and each weight ω_i obeys a standard normal distribution (μ_i, σ_i) ; $P(\omega)$ is the prior distribution of the weight under different investment risks.

In this paper, historical power grid infrastructure projects in Hunan, China, are presented to validate the effectiveness of the proposed project duration prediction method with multi-factor investment risks. The posterior distribution of weights in the BNN-based duration prediction model varies with the probability of risk occurrence. Then, the occurrence probability distributions of project duration delay under different investment risks can be extracted from a large amount of sampling data from Monte Carlo analysis, and the resulting project delay probability distributions are shown in Figure 1.

In Figure 1, it can be found that number of delay months is increased with the growing investment risk. On the other hand, the delay months of infrastructure projects under financial risk usually have a small standard deviation, and the project delay probability under extreme climate is the highest. The results show that the number of delay months can reach 10 months, and this is because electricity demand changes will lead to variation in design processes and technologies.

5 Discussion and conclusion

Based on the statistical analysis of practical infrastructure projects data in Hunan, China, the following are the key findings of this study: 1) the project delay is more likely to occur in backcountry, and the delay rate can be up to 43%; 2) risk of infrastructure project delay rises as the voltage level increases. The delay rates with voltage levels 35 kV, 110 kV and 220 kV are 26%, 29%, and 35%, respectively; 3) timely investment will accelerate the construction rate of infrastructure projects, thereby reducing the probability of delay; 4) the larger the planning capacity is, the lower the degree of timely investment will be. Risk of infrastructure project delay decreases as the curve coordination degree increases; and 5) further research will focus on the diversity of investment risk factors and combined effects of multiple risk factors on power grid infrastructure planning.

Author contributions

Conceptualization, KS and CX; data curation, JS and YL; formal analysis, ZZ; methodology, YW; visualization, CL and LC; writing—original draft, JS and ZZ; writing—review and editing, KS.

Funding

This work is supported by the State Grid Science and Technology Project (no. 5100-202123009A).

Conflict of interest

Authors KS and CX were employed by State Grid Hunan Electric Power Company Limited. Authors JS, YL, CL, and LC were employed by State Grid Hunan Electric Power Company Limited Economic and Technical Research Institute.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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